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Using the health belief model to assess the willingness to pay for urban heat island mitigation measures : The case of a Miyawaki micro-forest in Nantes

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Abstract

In light of an escalating global warming, this study investigates individual perceptions towards heat waves (HWs) risks and their mitigation measures (MMs), particularly concerning urban heat islands (UHIs) in Nantes, France. Using the Health Belief Model (HBM) and the Contingent Valuation Method (CVM), we aim to study the influence of health-related beliefs about HWs on individuals' willingness to pay (WTP) for a proposed urban micro-forest (UMF) using the Miyawaki technique. Data were collected through an online questionnaire, and despite limitations, several insightful findings emerged. The study revealed widespread awareness of HWs threats and benefits of MMs, although HBM's impact on WTP was less pronounced with perceptions of lower benefits and higher barriers influencing WTP. Finally, this study underscores the complex interaction between individual beliefs and socioeconomic characteristics, in dictating public receptivity towards environmental initiatives such as UMFs.

Résumé

À la lumière de la montée en puissance du réchauffement climatique, cette étude examine les perceptions individuelles des risques liés aux vagues de chaleur et de leurs mesures d'atténuation, en particulier en ce qui concerne les îlots de chaleur urbains (ICU) à Nantes, en France. En utilisant le modèle des croyances en matière de santé (HBM) et la méthode d'évaluation contingente (MEC), nous visons à étudier l'influence des croyances en matière de santé concernant les vagues de chaleur sur le consentement à payer (CAP) des individus pour une proposition de microforêt urbaine (MFU) utilisant la technique de Miyawaki. Les données ont été recueillies au moyen d'un questionnaire en ligne et, en dépit de certaines limites, plusieurs résultats intéressants ont été obtenus. L'étude a révélé une prise de conscience généralisée des menaces liées aux vagues de chaleur et des avantages des mesures d'atténuation. Toutefois, l'impact du HBM sur le CAP est moins prononcé, avec des perceptions d'avantages moindres et d'obstacles plus importants qui influencent le CAP. Enfin, cette étude souligne l'interaction complexe entre les croyances individuelles et les caractéristiques socio-économiques, qui dicte la réceptivité du public à l'égard d'initiatives environnementales telles que les MFU.

Keywords : *Heat waves ; Urban heat islands ; health belief model ; willigness to pay ; Contingent valuation method ; Nantes*

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Summary

Introduction

In 2022, France experienced one of the most unprecedented and severe summer ever recorded in his history. With a total of nearly 3,000 deaths, the summer of 2022 turned out to be the deadliest since 2003[1]. Indeed, due to climate change, climate threat has never been as significant as today. As a matter of fact, empirical evidence shows a growing incidence of extreme events in recent years. Among these events, Heatwaves (HWs) have proven to be particularly devastating in terms of their societal impact. It is important to note that HWs lacks of a singular, universally accepted definition, as its characteristics may vary depending on the geographical location and time of year. Nevertheless, it is generally acknowledged that a HWs denotes a period during which abnormally high temperatures persist for consecutive days or even weeks.

In the modern era, several HWs have left their mark on people's minds. Among these, probably one of the most well-known is the one that occurred in Europe during the summer of 2003. Affecting several European countries, this HWs has had dramatic effects on our societies. In France alone, this HWs was responsible for an estimated of 15,000 excess deaths. More generally, it stands as one of the deadliest natural disasters in the European modern history accounting for at least half of all the victims from climate-related events over the last four decades[2]. As highlighted by the 2003 HWs, HWs can have major consequences on human health and well-being in general. Among the most notable consequences, we find an increase in mortality and morbidity as well as the emergence of mental health issue. Thus, it is vital for our societies to take the matter of HWs seriously, at the risk of suffering heavy damage. While accurately quantifying the costs caused by HWs is challenging, the European Environment Agency (EEA) estimated that economic losses due to extreme weather events could be estimated between 450 and 520 billion euros for the 1980-2020 period[3]. Although these costs extend beyond healthcare expenses, they provide valuable insights

[1] Le Monde, "Avec trois épisodes de canicule, l'été 2022 est le plus meurtrier depuis 2003," 2022

[2] EEA, Economic losses from weather and climate-related extremes in Europe reached around half a trillion euros over past 40 years, 2022

[3] *ibid*

to understand how damaging these events can be for our society.

Considering the above-mentioned points, many questions can be raised regarding our attitude, as a society, towards climate events such as HWs during the next decades. This study focuses specifically at the effects that HWs can have on cities and their residents. Indeed, due to the way our cities are structured, cities exhibit greater vulerability to HWs. This vulnerability to heat is expressed by the phenomenon of Urban Heat Island (UHI). A city or an urban area will be classified as an UHI when it experiences warmer temperatures than surrounding rural areas. As a result, the negative externalities of HWs are amplified by cities and can severely impact their residents. However, cities are not necessarily bound to be UHI. In fact, by implementing ambitious mitigation policies, cities could become more livable during HWs episodes. In the context of this study, a mitigation policy refers to a measure aimed at reducing and or mitigating the impact of HWs on cities and their residents.

While the risks associated with HWs are numerous, individuals can significantly reduce these risks by recognizing them and taking simple precautionary measures such as drinking water, avoiding going out during the day or minimizing physical activities[4]. This raises the question of whether individuals truly take into account the risks associated with HWs and, if so, whether their perception of risk influences their behavior. In this study, our aim is to investigate whether health related beliefs, specifically beliefs about the impacts of HWs, can influence individuals' Willingness to Pay (WTP) for a UHI mitigation policy. The WTP refer to the maximum value that an individual would be willing to give to participate in the implementation of the policy. In this study, the mitigation measure will take the form of an Urban Micro Forest (UMF)using the Miyawaki technique. The Miyawaki technique, a Japanese botanical method that offers several advantages over conventional methods for mitigate UHI.

In order to address this issue, we have employed two primary methods. The first one, the contingent valuation method, widely used in the framework of environmental goods valuation, enables us to assign a monetary value to the UMF. To achieved this, we have designed a questionnaire that has been distributed to the residents of Nantes. Nantes was chosen as the target city for this study due to its status as one of the largest urban areas in France, thereby rendering it highly susceptible to the UHI effect. The decision to contribute to a UHI mitigation measure can be considered as

[4] Santé publique France, Vague de chaleur intense et durable sur le territoire : rappel des précautions à prendre par tous, 2022

a preventive health behavior in the sense that the measure will aim at mitigating the health and welfare effects of HWs Thus, in order to examine the health-related beliefs regarding HWs that might influence individuals' WTP, we will employ the Health Belief Model (HBM). The HBM is a psychological model widely utilized for explaining preventive health-related behavior and is very well suited to be used with the CVM as HBM components are generally obtained through a questionnaire. Since the perception of the risk of HWs and the determinants of the WTP are multi-factorial, the questionnaire we have designed also integrates questions related to the environmental sensitivity of individuals as well as questions related to their socioeconomic characteristics. This study can be considered novel in several ways. First, it is the first one to look at the WTP for HWs and/or UHI mitigation measures in a French city. Additionnaly, it is the first to use the HBM to assess the WTP for a mitigation measure. Indeed, while the use of a psychological model is not new to assess the WTP for UHI mitigation measures, previous studies have mainly relied on the the theory of planned behavior (TPB), another psychological model. Finally, this is the first study to look at the economic evaluation of a UMF using Miyawaki technique.

To address our research problem, we have structured this study in three main parts. The first chapter will provide an overview of the study's context. In this chapter, we will investigate the UHI causes and consequences. Additionnaly, we will review the methods that can be employed to mitigate UHI effects, including the Miyawaki technique as it will be at the core of our CVM. The second chapter is going to be dedicated to the methods we utilized. We will introduce both CVM and HBM as well as econometrical methods used to assess WTP for a UHI mitigation policy. This chapter will also provide a better understanding of the questionnaire structure that was developped to collect data. Finally, the third and final chapter of this study will be consecrated to the analysis and interpretation of the collected data. We will utilize statistical and econometrical techniques to analyze respondants' responses. The results will be presented and discussed, providing insights into individuals' WTP for the mitigation measures.

Chapter 1

The urban heat island effect : Causes, consequences and mitigation strategies

1.1 Climate change playing an exacerbating role

It is now a well-established fact that human activities, specifically through the emission of Green Houses Gases (GHG), have been a primary contributor to the global warming of the Earth's atmosphere. The current level of global warming is estimated to be 1.1° above pre-industrial levels, and if human activities continue at the current rate, this warming is likely to increase further until carbon neutrality is achieved. The Intergovernmental Panel on Climate Change (IPCC) has predicted five different scenarios, depending on how societies address climate change. Even in the most optimistic scenario, global warming is projected to approach 2° above pre-industrial levels, while in the worst-case scenario, it may exceed 4° by the end of the century. Therefore, climate change will have a significant impact on our society, regardless of the GHG emission scenario (IPCC, 2022).

Among many other issues, this increase in global temperatures impacts the likelyhood of extreme events, especially HWs and droughts (IPCC, 2022). For instance, in France the incidence of HWs in France - which was on average one summer every 5 years before 1989 - has become annual since 2000[1]. This trend has not decelerated as we have observed as many HWs in the last decade as in the second half of the 20th century[2]. HWs are also becoming more and more intense. Recent HWs - especially 2019 and 2022 - proved it by being 1.8° to 4° C warmer than if they had occurred

[1] Météo France, Vagues de chaleur et changement climatique, 2022
[2] *ibid*

a hundred years ago[3].

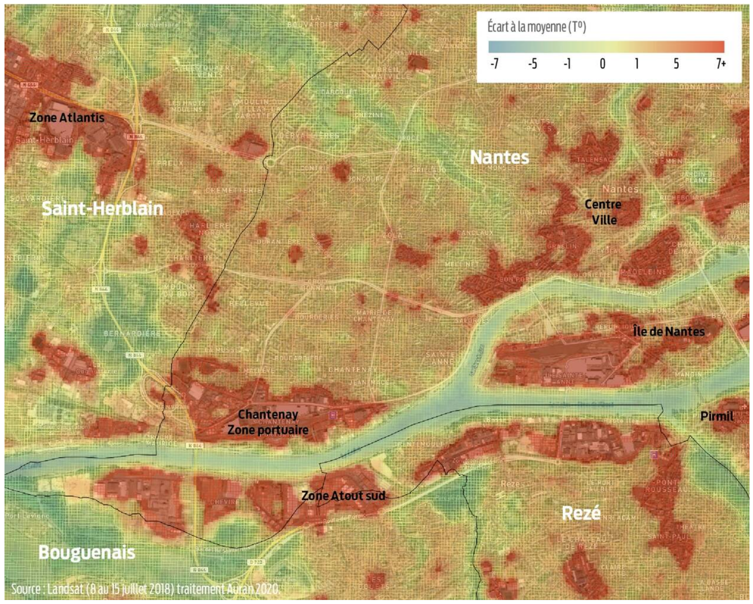
1.2 The urban heat island effect : Causes and consequences

Cities are among the areas that are most unfavorably impacted by global warming and the proliferation of HWs. This is due to the phenomenon known as the UHI effect. We recognize a UHI when a location's observed temperature is significantally higher than the temperature in surrounding rural areas. In some cities, the temperature difference between the urban area and the external rural areas can reach up to 8°C or plus. Figure 1.1 illustrates the impact of UHI on the city of Nantes and its surrounding region during the summer of 2018. As shown in the satellite image, temperature differences of up to 8°C above average can be observed, although vegetated areas or areas close to water exhibit lower temperatures.

The UHI phenomenon is not a recent issue. It has existed since cities and urban spaces began to be built. However, the problem is intensifying and accelerating due to the increased frequency and severity of HWs caused by global warming. Furthermore, this issue affects an increasing number of people because. On a global scale, 55% of the population currently resides in urban areas. By 2050, this figure is expected to rise to almost 70%. In France, the situation is even more pronounced, with nine out of ten individuals living in or close to urban areas[4].

[3] Météo France, Une vague de chaleur exceptionnelle par sa précocité et son intensité, 2022
[4] INSEE, En France, neuf personnes sur dix vivent dans l'aire d'attraction d'une ville, 2020

Figure 1.1: Impact of UHI on the city of Nantes and its surrounding area during the summer of 2018



Source: Landsat (8 au 15 Juillet 2018) traitement Auran, 2020

1.2.1 The causes of the UHI effect

The causes of the UHI phenomenon are numerous, but they all result from the way human societies have chosen to design and organize urban spaces. Occidental societies have built their entire functioning and economy around cities. As previously mentioned, in France, nine out of ten individuals reside in urban areas. Despite the increasing popularity of public transportation, 59% of urban residents still rely on cars as their primary mode of transportation to get to work, and this figure can approach 90% for individuals living outside city centers[5]. Additionally, due to urban sprawl[6], an increasing proportion of people live outside their municipalities of residence, resulting in high levels of car use to travel to and from the city[7]. All of these movements and economic activities generate anthropogenic heat that contributes to both GHG emissions and UHI through an increase in air temperature (Taha, 1997).

To accommodate this movement and economic activity, cities have undergone significant transformations. For example, to facilitate car access, a large number of roads, buildings, and parking lots

[5] INSEE, La voiture reste majoritaire pour les déplacements domicile-travail, même pour de courtes distances, 2021
[6] The spread of a city into the area surrounding it, often without planning, Cambridge Dictionary
[7] INSEE, De plus en plus de personnes travaillent en dehors de leur commune de résidence, 2016

have been constructed at the expense of natural areas. This substitution of nature with infrastructure has substantially reduced the evapotranspiration and cooling capacity of cities (Nuruzzaman, 2015). Additionaly, UHI effect is exacerbated by the materials used for constructing human infrastructures. Low albedo[8] materials - such as asphalt concrete - absorb solar energy and heat, leading to a rise in urban temperatures (Mohajerani et al., 2017).

Another significant factor that exacerbates the UHI effect is the architecture of our cities. Due to the high density of city centers and the size of buildings, heat is retained more easily, and air and wind have more difficulty circulating. Initially, a phenomenon known as *urban canopy* traps heat in the city (Oke, 1988). Then, due to the size and the density of buldings, it is followed by a *wind-blocking*, which reduces the cooling capacity of the wind and leads to a rise in temperatures (Rajagopalan et al., 2014).

1.2.2 The consequences of the UHI effect

Heatwaves can have various consequences that are exacerbated by the UHI effect. The primary effect that is immediately felt is the sharp increase in energy consumption, particularly electricity. This is because individuals require air conditioning to maintain comfortable indoor temperatures during hot weather. According to a study conducted in the Yangtze River Delta region in China, a 1°C increase in outdoor temperature on warm days can lead to a 14.5% rise in electricity consumption (Li et al., 2019). Nevertheless, this increase can differ by country and time period, with electricity demand increasing between 0.5% and 8.5% in other studies (Santamouris et al., 2015). Furthermore, litterature indicates that the UHI effect has a particularly significant impact on the peak energy demand. Depending on the energy mix of each country, such a spike in energy consumption may lead to a rise in GHG emissions. If countries such as France have the advantage of generating a significant portion of their electricity from low-carbon energy sources, others nations still rely on coal and other nonrenewable energies to produce electricity.

The second impact and maybe the most important of UHI is the one on human health and well-being. The UHI effect leads to a decline in well-being and global health by an increasing heat-related illnesses and fatalities. Generally, during periods of intense heat, the causes of death are not necessarily heat strokes, but a combination of morbidity, with heat playing an exacerbating

[8] Albedo is the measure of a surface's ability to reflect sunlight, often expressed as a percentage of the total amount of incoming solar radiation.

role, particularly for respiratory illnesses (Heaviside et al., 2017). Among the most common heat-related illnesses are cramps, fatigue, and respiratory difficulties (EPA, 2022). It is important to note that the impacts of HWs and UHI on individuals are not homogeneous, and factors such as age, gender or income significantly influence vulnerability. For instance, older and poorer individuals are more likely to suffer from heat-related consequences (D'Ippoliti et al., 2010). Additionally, research has shown that women are more vulnerable to heat than men (D'Ippoliti et al., 2010). We will talk of those aspects more deeply 2.3.2.

Heat impacts are not limited to physical health, as several studies have highlighted an increase in psychological disorders associated with heat. These disorders include psychological distress, anxiety, depression, and aggressive behavior, among others (Wong et al., 2018). In some cases, there is also an elevated risk of suicide (Thompson et al., 2018). Additionally, individuals who are already experiencing mental health issues may face a worsening condition due to heat exposure.

1.3 Review of UHI mitigation strategies

HWs are becoming increasingly frequent, and we must prepare to face this challenge in the futur. To reduce the vulnerability of our cities to HWs, several mitigation strategies can be implemented. It should be noted that we will only mention mitigation measures (MMs) that concern urban planning. Other MMs that aims at reducing anthropogenic heat won't be mentionned.

1.3.1 Using vegetations to mitigate the UHI effect

Re-vegetation of cities is perhaps the most effective method of controlling UHI. Revegetation can take two primary forms. The first form is the planting of trees *ex-nihilo*[9]. Trees can provide both environmental and social benefits. They contribute to temperature reduction in cities in several ways. By creating shaded areas, trees can cool the environment and save energy by reducing air conditioning usage. In one of the most well known study on this topic, researchers demonstrated how 16 trees could save household energy by providing shade to buildings (Akbari et al., 1997). Additionally, trees can cool the ambient air from 2°C to 8°C through evapotranspiration as shown by the French National Forest Office[10](ONF). They also possess excellent sun radiation absorption capability of up to 65% (Coder, 2011). Trees play a vital role in our environment as they facilitate transpiration, acting as natural air conditioners, while simultaneously absorbing CO_2 and purifying

[9] From scratch

[10] ONF, Le pouvoir des arbres : l'évapotranspiration, 2022

the air. In addition to their ecological benefits, trees have numerous economic and social qualities, including aesthetic value and noise reduction capabilities. However, there are certain drawbacks to relying on trees as a solution. For instance, the growth rate of trees is comparatively slow, and it may take several years before their full advantages can be fulfilled. Furthermore, depending on the species of trees and the local climate, the costs of maintenance and disease control can be significant. While there may be additional challenges associated with the use of trees as a solution, such issues are often contextual and hence, difficult to enumerate.

The second most commonly adopted method for revegetation involves the use of green roofs, which can be categorized into two types, extensive and intensive. Extensive green roofs have narrower coverage, and thus are comparatively less effective in combating heat. However, they have advantages in terms of their cost-effectiveness and ease of maintenance. In contrast, intensive green roofs are larger, more complex, and offer significant advantages in mitigating UHI and combating HWs. Among the most frequently cited benefits of green roofs are improved stormwater management, better temperature regulation within buildings, reduced UHI effects, and increased urban wildlife habitat (Oberndorfer et al., 2007). Moreover, the surface temperature of a green roof can be up to 4° Celsius lower than that of conventional roofs (EPA, 2008c). This gives buildings the opportunity to reduce their electricity consumption for cooling purposes (Susca et al., 2011). Similarly to trees, green roofs also have certain limitations. Firstly, their initial cost is usually higher than that of traditional roofs. However, this cost is quickly offset by the savings in electricity consumption for cooling (EPA, 2008b). Additionally, studies have identified several challenges associated with green roofs, such as high construction and maintenance costs as well as a possibility for roof leakage (Shafique et al., 2018). Finally, some research have noted that green roofs may have detrimental effects on water quality due to nutrient leaching (Hashemi et al., 2015).

1.3.2 The particular case of the Miyawaki technique

The Miyawaki technique was originally developed by Akira Miyawaki in the 70s for reforestation of large industrial sites in Japan. The method proved to be highly effective in Japan, and Miyawaki continued to promote it throughout the Japanese archipelago (Miyawaki & Golley, 1993). However, it took some time for the method to be adopted in Europe and France. The method was first implemented in Paris in 2018, and since then, it has gained significant popularity and been experimented in many other French cities, including Lyon, Toulouse, or Nantes. This gain in popularity of the Miyawaki technique in France can be attributed to multiple factors such as the emergence of various associations such as Urban Forest or MiniBig Forest - which have partnered with public entities to establish micro-forest projects - but also the growing need for urban areas to re-vegetate their cities to bring back cool and biodiversity.

The Miyawaki technique is based on the principle of Potential Natural Vegetation (PNV), which refers to the vegetation that would have existed in a particular location if there had been no human intervention. The objective of this method is to select trees and plant species that would have been naturally present at the location of the future forest. By selecting trees and plant species based on PNV, the Miyawaki method ensures that the forest is composed of native species that are well-adapted to local conditions, which in turn is suppose to enhances biodiversity and promotes the forest's long-term resilience against environmental stressors and disturbances.The objective of this method is to recreate the same mechanisms present in a primary forest. To do so, it is generally recommanded to follow the following steps. The first step in the Miyawaki method is to observe the surrounding area of the future forest to identify the species that are naturally present. After this step, it is necessary to fertilize the soil to ensure that the soil is as fertile and rich as possible. The final step of the Miyawaki method is to recover the selected shoots and plant them. The planting stage is crucial to achieve the densest forest possible. It is generally recommended to plant an average of three trees of different strata (i.e., different sizes) per square meter.

The Miyawaki method is supposed to offer several unique benefits that are not achievable through conventional reforestation methods. For instance, planting trees of different strata very close together allows each tree to capture sufficient light for its growth and development. The proximity of the trees creates healthy competition between them, which results in a much higher growth rate than that of trees in a conventional forest. This, in turn, results in a Miyawaki forest being denser and containing more diverse vegetation and biodiversity than conventional forests. Furthermore, Miyawaki forests are highly resilient and have been observed to recover quickly from natural disasters such as earthquakes and fires (Miyawaki & Golley, 1993). This resilience is due to the high biodiversity and rapid growth rate of the forest, which enables it to recover quickly from environmetal hazards. However, this choice comes with a cost since the mortalility rate of threes seems to be very high. In a study conducted in Italy, researchers comes with a mortality rate of 61% and 84% after 12 years for two micro-forest (Schirone et al., 2011). The second main advantage of an UMF is that they are easy to maintain. In fact, according to BoomForest, maintenance of an UMF is only required during the first three years after planting. The Miyawaki method is particularly relevant in an urban environment as these forests do not require large spaces to be effective. According to MiniBig Forest, only 200 square meters is needed to build such a forest, making it a suitable approach in urban areas where space is limited[11]. Thus, Miyawaki's UMF are a good way to mitigate UHI by constituting cooling places. Unfortunately, there are few studies available that examine UMF in depth. Therefore, while it is known that the Miyawaki method allows for the rapid creation of coolling spaces, it remains challenging to establish whether this approach is more advantageous in the long term than traditional methods, particularly concerning biodiversity and cooling capacity.

1.3.3 Using cool materials to mitigate the UHI effect

Another approach to mitigate the UHI effect is through the use of cooler materials in urban areas. The key advantage of using cooler materials is that they typically have a higher albedo compared to traditional materials like asphalt concrete. The first and most commonly used type of cool materials are cool roofs, which are designed to reflect sunlight as much as possible. These roofs are often white in color, as white materials have the lowest solar reflectance. The primary benefit of using cool roofs is that they reduce energy consumption by transferring less heat to the building (Konopacki et al., 1998). Since the peak in electricity demand occurs during the daytime in summer, the use of cool roofs can help reduce the magnitude of this peak. Similar to other MMs, cool roofs can also lower air pollution and GHG by reducing energy consumption (Akbari et al., 2005). Like all other methods, the implementation of cool roofs incurs initial costs at the time of purchase, which may be higher than traditional roofing materials. However, these costs are ultimately recouped by the energy savings achieved through the use of cool roofs. One significant drawback of cool roofs is that they reflect heat, which could lead to increased heating demands during winter months (Kolokotroni et al., 2013)). Nevertheless, this effect does not seem to be strong enough to outweigh the benefits of cool roofs in summer (EPA, 2008b).

Another application of cool materials is in pavement. Various materials can be used for pavements, but it is essential to select materials that are reflective and preferably permeable. Like the previous methods, the use of cool pavements reduce energy consumption, lower GHG emissions, and improve air quality. However, quantifying the energy savings achieved through cool pavements is more challenging than with cool roofs. Unlike cool roofs, it is difficult to conduct a controlled experiments involving the measurement of energy consumption before and after the installation of cool pavements. Cool pavements have the unique benefit of improving water quality and reducing the risk of flooding by managing stormwater runoff[12] (Santamouris, 2013). Compared to

[11] MiniBig Forest, La Méthode Miyawaki
[12] Precipitation (rain or snowmelt) that flows across the land

traditional methods, cool pavements also have a longer lifespan and reduce waste (EPA, 2008a). Similar to vegetal solutions, cool pavements also offer improvements in quality of life, such as nighttime illumination (Pomerantz, 2000) and increased safety for drivers (Elvik & Greibe, 2005). The costs of cool pavements are relatively similar to those of traditional methods, with a possible extra cost depending on the specific characteristics and location. However, it seems that the potential energy and comfort savings that can be achieved through cool pavements compensate for any additional costs (Pomerantz, 1997). Despite their benefits, cool pavements also have some disadvantages. Due to their reflective characteristics, cool pavements can sometimes reflect light and project it onto surrounding buildings, resulting in an increase in their temperature (Qin, 2015a). In fact, one study has shown that the higher the albedo of a pavement is, the higher the cooling load required to cool the near building will be (Qin, 2015b).

1.3.4 Summary of Chapter 1

To improve the clarity and comprehensibility of this chapter, we have included a summary section with two tables. Table 1.1 presents a comprehensive overview of the causes and effects of UHI phenomenon, as discussed in Sections 1.2.1 and 1.2.2. This table provides also a description for each cause and consequence. Additionally, Table 1.2 plays a similar role, focusing on the content covered in Section 1.3. It emphasize the advantages and disadvantages associated with two mitigation approaches that were explored, the utilization of vegetation and cool materials.

Table 1.1: Summary of Urban Heat Island Causes and Effects

Causes	
Cause	**Description**
Anthropogenic heat generation	Increased GHG emissions and air temperature due to human activities
Infrastructure replacing natural areas	Reduced evapotranspiration and cooling capacity in cities
Low albedo construction materials	Absorption of solar energy and heat, leading to higher urban temperatures
Urban architecture	Heat retention and reduced wind circulation due to Urban Canopy and wind-blocking
Effects	
Effect	**Description**
Increased energy consumption	Increase in electricity consumption leading to a potential rise in GHG emissions
Decline in human well-being and health	Heat-related illnesses + Excess mortality
Psychological disorders	Increased risk of distress, anxiety, depression, aggression, and suicide

Table 1.2: Summary of Urban Heat Island Mitigation Strategies with Advantages and Disadvantages

Mitigation Strategies		
Strategy	**Advantages**	**Disadvantages**
Using vegetation	• Reduces heat • Saves energy • Improves air quality • Aesthetic value • Noise reduction	• Slow growth rate of trees • Maintenance and disease control costs • High upfront construction and maintenance costs for green roofs • Roof leakage and nutrient leaching risks
Using cool materials	• Reflects sunlight • Reduces energy consumption • Improves air quality • Longer lifespan for cool pavements • Nighttime illumination and increased safety	• Possible increased in heating demand during winter for cool roofs • Light reflection onto surrounding buildings • Slightly higher initial costs

Chapter 2

Theoritical framework and survey design

2.1 The contingent valuation method

2.1.1 Context and application

Why do we use the contingent valuation method ?

In the previous chapter, various methods were discussed for mitigating the UHI phenomenon. Many of these methods utilize nature and vegetation as a means to combat UHI. It has been observed that vegetation and trees can reduce local temperatures, improve air quality, promote biodiversity, and enhance the urban landscape. However, all of these benefits are positive externalities and do not provide a market valuation. As a consequence, a significant information asymmetry is created for economic agents, making it challenging to make decisions when the benefits of these methods are not easily visible or quantifiable.

This information asymmetry may have contributed to the concrete-based development of urban areas. As a matter of fact, it is relatively easy to estimate the benefits of constructing a road or business center compared to the destruction of a forest or natural area. Nonetheless, the scientific literature has investigated the economic value that can be attributed to natural environments, and two primary types of services rendered by natural environments have been identified: use value and non-use value. The use value can be direct, indirect, or induced. Direct use value refers to the direct consumption of the good, such as fruit trees or recreational activities like acrobranche. Indirect use value relates to the indirect benefits derived from the presence of a natural space, such as shaded areas created by trees. The induced value corresponds to the use of the good as a factor of production, such as utilizing trees to generate energy. The non-use or preservation value is based on ethical or altruistic reasons. For instance, legacy value is the preservation of a primary forest for future generations, while the option value is the potential to benefit from the forest in the future. Lastly, the value of selflessness availability is the value created by the preservation of the forest for others to benefit in the future (Banos & Rulleau, 2014).

Once the use or non-use value of a non-market good has been defined, different methods exist to estimate its monetary value. These methods can be categorized into two types: revealed and stated preference methods. Revealed preference methods enable us to evaluate the value of non-market goods based on an existing substitute market. More specifically, we rely on the observable choices of individuals in reality and assume that we can establish preferences from these choices. The two most commonly used methods for valuing a good using revealed preferences are the travel cost method and the hedonic pricing method. The travel cost method considers that the demand or preference for a natural environment can be assessed through the expenditures incurred by individuals in traveling and visiting that environment. This method was initially proposed by Hotelling (1947) in the context of American national parks. On the other hand, the hedonic pricing method attempts to value environmental assets using the real estate market. It assumes that the value of a property depends on various characteristics or amenities, and that the price differences observed between several properties could be explained by the presence or absence of certain environmental characteristics. For example, a house near the sea could have a higher price than one that is further away. Similarly, it is interesting to observe the real estate market between a heavily polluted area and a non-polluted area, as this can allow us to see the value placed on air quality (Salles, 2020).

In situations where it is not possible to refer to a market of substitutes, it becomes necessary to simulate the existence of a market that offers one or many goods or services. Creating a hypothetical market allows us to identify individual preferences. To obtain these preferences, a questionnaire is typically used to identify an individual's WTP or to accept (WTA) for the hypothetical market situation. There are mainly two types of methods for this type of evaluation: Contingent Valuation Method (CVM) or choice modelling methods (CM) (Riera et al., 2012).

The CVM was first conceived by Ciriacy-Wantrup, 1947 to evaluate capital returns from soil-conservation practices but was first used by Davis, 1963 to determine the value that hunters might place on a recreational area where they can hunt. He was the first to use a direct questionnaire for this purpose. In the following years, the method gained in popularity and became one of the most widely used methods in environmental economics. To address some limitations - which we will discuss in the next section 2.1.2 - and to offer an alternative to the CM, another stated preference has been developed, the CVM.

In both methods, we seek to determine the WTP/WTA - the amount of money that an individual would be willing to pay or accept - in exchange for a certain good or service[1]. However, these two methods differ in a few points. While in a CM the inclusion of price/cost as a good allows for the indirect recover of in-

[1] In economic terms, we are attempting to find the consumer surplus.

dividuals' WTP/WTA through their rankings, ratings, or choices (Hanley et al., 2001), the CV ask directly to respondants their WTP/WTA for a particular good or service. Thus, a CM does not allow researchers to personalize and be as specific as a CVM. In a CM, we ask respondents to choose between several options, whereas in a CV, we build a more precise, better defined project.

Stated preferences methods has two major advantages over the revealed preferences methods mentionned above (Scherrer, 2002). The first advantage is that they can be used *ex ante*, i.e to estimate the value of a good or service before it is even implemented. Thus, this method can serve as a prospect for policymakers seeking to determine which measures will be most favorably accepted by their population. The second advantage is that this is the only method that allows the assessment of the non-use values discussed above.

2.1.2 The limitations of the contingent valuation method

Like all methods, the CVM is subject to several biases and limitations. According to the meta-analysis of Venkatachalam, 2004, the CVM is subject to various types of biases that can affect both the validity and reliability of the experimentation. While the number of biases that can affect these two aspects is large, our goal is not to provide an exhaustive list but to present the main ones.

The fundamental difference between willingness to pay and to accept

As previously mentioned, in a CVM, we can be interested in both WTP and/or WTA. This choice is crucial because it can significantly impact the results of our study. It has been observed that the amount attributed to the same hypothetical good or service is generally higher when using a WTA than a WTP. While there are many possible explanations for this difference, three important effects are highlighted : income effect, substitution effect and loss aversion effect. The income effect explains why the values of WTP are generally lower than WTA because the choice of individuals is subject to a budget constraint, which is not the case with WTA. According to the substitution effect, if the hypothetical good or service is highly substitutable - i.e. can be easily replaced by a similar good/service - then the difference between WTP and WTA converges and tends to get smaller. On the other hand, for public goods or services with very low substitutability, such as reduced health risk, the difference between the two persists and is significant (Shogren et al., 1994). Finally, the WTA's value may be greater due to loss aversion because, as described by Tversky and Kahneman, 1991, losses incurred by individuals - what they pay - have more impact on preferences than gains. Thus, the WTP of an individual tend to be lower than his WTA. The CVM also faces what is called hypothetical bias, which is one of the biggest problems with this method. If a study suffers from hypothetical bias, it means that the WTP measured in the study is overestimated compared to the true WTP of the respondents (Cummings, 1986). However, measuring hypothetical bias is challenging because it requires putting the respondents in a real situation.

The importance of the scenario

In addition to biases mentioned earlier, the nature of the CVM scenario itself can also introduce biases. For example, we say that there is an embedding effect when there is a difference depending on whether the good or service is presented as a single item or as a package. For instance, Kahneman and Knetsch, 1992 showed that the WTP of Toronto citizens to clean up all the lakes in Ontario was only slightly higher than the WTP to clean up the lakes in the - much smaller - Muskoka region. Biases may also arise from the order in which assets are presented. Some CVM may present multiple assets at once, so the order in which assets are presented to the respondent will have an impact on the WTP value. For example, in a study presenting different health care aid programs, Stewart et al., 2002 concluded that the order in which the programs were presented did have an impact on the WTP of individuals. Different reasons can explain such a difference, in the case of aid programs, the authors hypothesized that individuals should feel a form of social moral obligation after having contributed to the first program. Finally, it seems that the information provided in the CVM is a source of bias. The information provided and how the good is presented plays a very important role in the value of the WTP. Many studies have examined the relationship between information quality and WTP. For example, in a study on the effect of information about animal welfare on consumer WTP for yogurt, Napolitano et al., 2008 found that consumers were influenced by low standards of animal welfare, and when a yogurt was offered that was not very acceptable in terms of animal welfare, consumers tended to give a WTP that matched their expectations.

Inconsistency between elicitations methods

A major type of bias in CVM concerns the elicitation[2] method used for WTP/WTA. According to the literature, four main types of payment methods can be distinguished (Venkatachalam, 2004). The oldest method for eliciting WTP/WTA is the bidding game. The bidding game consists of offering each participant a random amount of money from a pre-determined selection. The respondent is asked to say *Yes* or *No* to each amount, and the game stops when the person says *No*. The highest amount to which the respondent says *Yes* will be considered as the individual's maximum WTP/WTA. While this method has the advantage of simulating a real market situation and obtaining the maximum value that an individual would be willing to pay or to accept, it has the disadvantage of being more complicated to implement and is really hard to use in online surveys (Cummings, 1986). Moreover, this method may be subject to anchoring bias - as described by Tversky and Kahneman, 1974 - which means that the WTP/WTA of individuals will tend to be influenced

[2] Mean of payment

by the initial value. Thus, a higher initial bid or anchor will result in a higher WTP/WTA.

The second and most popular approach is the payment card approach. This method consists of proposing various amounts to respondents, among which they must choose their maximum WTP/WTA. The proposed values generally start at 0 and increase at regular intervals (Boyle & Bishop, 1988). This method has the advantage of being very simple and usable via an online questionnaire. On the other hand, it could be biased by the chosen intervals (range bias) or by the central value (centering bias). However, few empirical works support the presence of such biases in the payment card method (Rowe et al., 1996).

Another popular method for collecting WTP/WTA is through open-ended questions. This involves asking participants directly the maximum amount of money they would be willing to pay or to accept to contribute to the public good or to policy. This method is controversial because, while it is simple to implement and does not involve anchoring bias, it can generate a large number of non-respondents. As a matter of fact, estimating a WTP/WTA accurately requires a lot of effort from an individual, and they may not be inclined to do so, especially if there are no incentives for doing it (Carson et al., 1996).

The last major type of method used to elicit WTP from individuals is closed-ended or dichotomous choice questions. This method asks respondents if they would be willing to pay or accept a certain amount of money for a specific good or service. We call this method *take-it or leave-it* because respondents must answer *Yes* or *No* to the question. The disadvantage of this method is that the answers give us poor information about the true maximum WTP/WTA of an individual. Thus, for the method to be effective, an extremely large sample size is required (Herriges & Shogren, 1996). To offset the weaknesses of this method, several follow-up questions can be added to the process, such as double-bounded, one-way street-up, and one-way street-down questions (Herriges & Shogren, 1996). Nevertheless, follow-up questions could be subject to anchoring bias as well as acquiescence bias[3] (Ready et al., 1996).

2.1.3 The contingent valuation method in practice

Miyawaki urban micro-forest (UMF) are a type of non-market goods that provide non-market services, as discussed in 1.3.2. Therefore, one of the methods mentioned above can be used to value this good. In this particular case, it would be irrelevant to use a revealed preference method as our objective is to determine the valuation of a good that does not yet exist. Thus, we have to choose between the CM and the CVM. Given the complexity associated with the CM and the unavailability of necessary tools during the study, we chose to use the CVM. Nevertheless, if we had the opportunity to use the CM, we could have imagined proposing to respondents to choose between two different methods to mitigate the effects of UHIs. For example, we

[3] IPOS, A systematic bias in data caused by some respondents tending to agree with whatever is presented to them.

could have given the choice between vegetation methods and cool material methods, leaving the opportunity for the status quo.
To apply the CVM, we designed a survey that we've divided into four main sections. The first, second, and fourth sections focus on the determinants of WTP, which are the characteristics that influence individuals' WTP. The second section, which we will describe in this part, is dedicated to the CVM.

The first step in the CVM was to describe the good that we submitted to respondants. We had to ensure that respondents were familiar with the good and had maximum information about it. Therefore, we provided a brief description of the Miyawaki technique, including its advantages and disadvantages. Making the good familiar to the respondent is a crucial step, as this can reduce hypothetical bias, as stated by Mitchell et al., 1989. We also asked respondents: *Aviez-vous déjà entendu parler de la méthode de Miyawaki avant de répondre à cette enquête ?* to identify the initial level of familiarity of the participants.

Then, we presented our hypothetical scenario to the participants. A good scenario should be as realistic and clear as possible to minimize the level of uncertainty of the respondents (Cummings, 1986). Therefore, we included as many elements as possible regarding the location of the site, its characteristics, etc. In order for the citizens of Nantes to recognize the location clearly, we included a 3D projection (Figure 2.1), a satellite map image (Figure 2.3), as well as a photo of the place (Figure 2.2).

Scenario

La ville de Nantes envisage la construction d'une micro-forêt de Miyawaki dans le centre-ville pour contribuer à l'amélioration de l'environnement urbain, réduire les îlots de chaleur, améliorer la qualité de l'air, favoriser la biodiversité et offrir un habitat pour la faune et la flore locales. Cette micro-forêt sera composée d'une grande variété d'arbres et d'arbustes soigneusement sélectionnés en fonction de leur adaptabilité au climat local et de leur capacité à fournir des avantages environnementaux. Le projet prévoit la plantation de la micro-forêt sur une surface d'herbe plane dans le centre-ville, entre le Boulevard Jean-Philippot et le Quai de Turenne. L'emplacement sélectionné, proche de l'hypercentre, offre un espace idéal pour la création d'une telle forêt. L'emplacement ainsi que des photos du lieu sont disponibles ci-dessous.

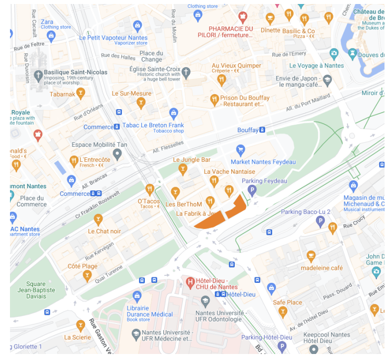
La surface sélectionnée pour la micro-forêt de Miyawaki mesure environ 1600 m², ce qui permettra de planter environ 4800 arbres et arbustes sélectionnés (3 arbres par m2 environ). Néanmoins, ce projet engendra un coût pour la ville de Nantes en lien avec l'achat des arbres et des arbustes, la location des équipements de plantation, le transport, l'irrigation, l'entretien et autres frais annexes. La municipalité de Nantes prévoit de collaborer avec une association spécialisée dans la création de micro-forêts de Miyawaki pour la mise en place de ce projet.

Google Earth

Figure 2.1: Caption for the 3D view

Google Earth

Figure 2.2: Caption for the earth view



Google Maps

Figure 2.3: Caption for the maps view

After presenting the scenario, respondents were asked the following question: *Dans le cadre de cette etude, nous souhaitons savoir si vous seriez dispose(e) a contribuer financierement a la construction de cette micro-foret dans le centre-ville de Nantes. Si oui, a quel montant seriez-vous pret(e) a donner ? Veuillez noter que la participation financiere prendrait la forme d'un financement participatif unique.*

In this study, we followed the recommendations of Arrow et al., 1993 and opted for the use of WTP instead of WTA. Regarding the payment method or elicitation, we used a mix of payment card approach and open-ended approach. For the payment card approach, we proposed amounts ranging from 0 to 100 with intervals of 10. We also included the option *Do not know/Do not wish to respond* to avoid the Acquiesence bias (Or Yea-Saying) bias. To differentiate real zeros - individuals who do not wish or cannot contribute to the project - and protest responses - individuals who disagree with the proposed scenario and are *de facto* against it - we asked those who did not wish to contribute the following question : *Vous avez indique(e) que vous ne souhaitiez pas contribuer financierement a la creation de la micro-foret de Miyawaki a Nantes. Pourriez-vous nous indiquer la ou les raisons de cette decision ?*. Based on the responses to this question, we will be able to distinguish between true and false zeros.

2.2 Using the health belief model to assess the willingness to pay

Once we have successfully estimated the value that our respondents could give to the construction of a Miyawaki micro-forest, we can focus on the determining factors in this decision. In this study, we have decided to examine one major factor, that can be subdivided in multiple ones. This factor is the HBM.To put it simply, we will use the HBM to try to understand and explain the individuals' WTP for this Mitigation measures (MMs)

2.2.1 Introducing the health belief model

The HBM was originally developed in the 1950s by the U.S Public Health Service. The model was designed to respond to the observation that people were not making efforts to participate in prevention or disease detection programs (Rosenstock et al., 1994). The researchers' goal was to raise awareness among individuals about certain diseases that were avoidable and had serious health consequences. They wanted to help people understand that they could drastically reduce the risks of such diseases by taking certain actions (Green et al., 2020). Over time, the model gained popularity and became one of the most widely used models for explaining preventive health-related behavior. Health-related behavior, in this context, can be defined as *any activity undertaken by a person who believes himself to be healthy for the purpose of preventing disease or detecting disease in an asymptomatic stage*(Kasl & Cobb, 1966). As a result, the HBM has been used in many studies related to issues like cancer screening behaviors, risky sexual behaviors, or more recently, the use of the Covid vaccine.

The HBM is usually employed in the medical field, but its applicability can be extended to HWs and UHI, as these phenomena have direct consequences on human health and well-being. Thus, the HBM provides a useful framework for understanding the health-related beliefs of individuals concerning HWs. Ultimately, the aim of this study is to determine whether such beliefs influence preventive health-related behavior, specifically the willingness of individuals to contribute to a project aimed at mitigating the negative effects of HWs and UHI. While the HBM use remains rare in the field of the environment, previous research has employed this model to identify predictors of risk perception and adaptive behaviors concerning HWs in Adelaide, Australia (Akompab et al., 2013). However, such studies did not propose an economic application and did not use a CVM. Therefore, to the best of our knowledge, this study is the first to use the HBM to assess the WTP for an UHI mitigation measure, especially a Miyawaki UMF.

However, other studies have used psychological models to assess individuals' WTP for UHI. For instance, Zhang et al., 2019a used the Theory of Planned Behavior (TPB) to assess individuals' WTP for green roofs. The author used the same methods but this time for cool roofs in Zhang et al., 2019b. The TPB is a psychological theory that states that individuals' intentions to perform a given behavior are based on their attitude towards the behavior, the subjective norm of performing this behavior, and their perceived behavioral control. To obtain these three factors that explain an individual's intentions, specific questions can be asked through a questionnaire. The TPB is one of the most commonly used theories in environmental economics to incorporate behavioral factors. For instance, the subjective norm component of this model is considered a key variable since it has been found to be highly predictive in various models (Conner & Norman, 2022). While the use of TPB could have been valid in this study, we chose to use the HBM as it is generally more specific to health-related behaviors. However, it would be interesting to conduct a similar study with the TPB. This would allow us to compare the results and see if one model performs better than the other. Finally, if there is a large number of psychological models, these two are still the most used.

2.2.2 The various components of the health belief model

In order to explain preventive health-related behavior, the HBM usually relies on five components. Like many psychological models that study individual behaviors, one way to construct these components is to integrate them into a questionnaire. This is what we did in our study by incorporating all of the HBM components into the second part of our questionnaire. For each component, respondents were presented with several statements to which they had to respond using a symetric Likert scale. A symetric Likert scale can be presented as follow :

Strongly Disagree (SD) - Disagree (D) - Neither agree or disagree (N) - Agree (A) - Strongly Agree (SA)

We used this type of scale to quantify respondant opinions, which in this case is the level of agreement regarding proposed statements. The scale is said to be symmetrical because the *N* option is in the middle of the responses. By doing this, we give each participant the independence to choose between any response in a balanced and symmetrical way (Joshi et al., 2015). We will now present each component of the HBM.

Perceived threat

The first component of the HBM is Perceived Threat (PT), which can be divided into two sub-components: perceived susceptibility or vulnerability (PV) and perceived severity (PS). In the context of our study, PV can be defined as the beliefs about the chances of experiencing a health issue related to heat. To measure this, we asked various questions related to both personal susceptibility and the individual's immediate environment, such as housing, urban infrastructure, and health services.

The second element of the PT construct is the perceived severity (PS). In the context of our study, this component can be defined as the belief regarding the severity of experiencing health issue related to heat. The purpose of this sub-component is to expose the beliefs held by individuals regarding the gravity of the potential consequences of HWs. Specifically, we aim to investigate whether individuals believe that HWs can result in severe, and possibly irreversible, outcomes with respect to their health and lifestyles. The consequences we consider include, but are not limited to, skin cancer, fatigue, anxiety, and the ability to work.

As previously discussed, PV and PS can be regarded as an individual's PT Champion, Skinner, et al., 2008. When considered together, these elements play a important role in the study of behavior. If an individual's beliefs suggest that they do not perceive themselves as vulnerable to HWs and that any potential exposure is unlikely to have a significant impact on them, their propensity to take action may be reduced. Consequently, individuals with a high level of PT are expected to be more prompt to engage in a preventive health-related behavior.

Perceived benefits

The second component of the HBM is Perceived Benefits (PB). This component refers to an individual's beliefs regarding the potential advantages of implementing a cooling strategy, such as a miyawaki UMF. The relevance of this component relies in the fact that a person is less likely to participate in the construction of a cooling island if they do not perceive any benefits. These benefits may include those related to health and the mitigation of HWs, as well as more implicit benefits such as aesthetic appearence or the pride associated with the implementation of a mitigation measure that an individual can feel. Consequently, it is anticipated that individuals who perceive the greatest benefits from the installation of MMs will also be the most involved in its implementation phase. For instance, Akompab et al., 2013 found that individuals with a high level of PB were more inclined to exhibit adaptive behaviors during a HWs.

Perceived barriers

The third component of the HBM corresponds to Perceived Barriers (PBARs). This component concerns an individual's beliefs regarding the potential obstacles or negative aspects that may arise from the implementation of coolling strategies. These barriers refer to elements that could potentially prevent individuals from taking action and contributing to the development of a mitigation measure. They may include tangible factors related to the effectiveness and relevance of mitigation strategies, as well as personal factors such as income or social influence. As for the PB, it is expected that individuals with a high level of PBARs will be less likely to contribute to the implementation of a mitigation measure such as the construction of a Miyawki micro-forest.

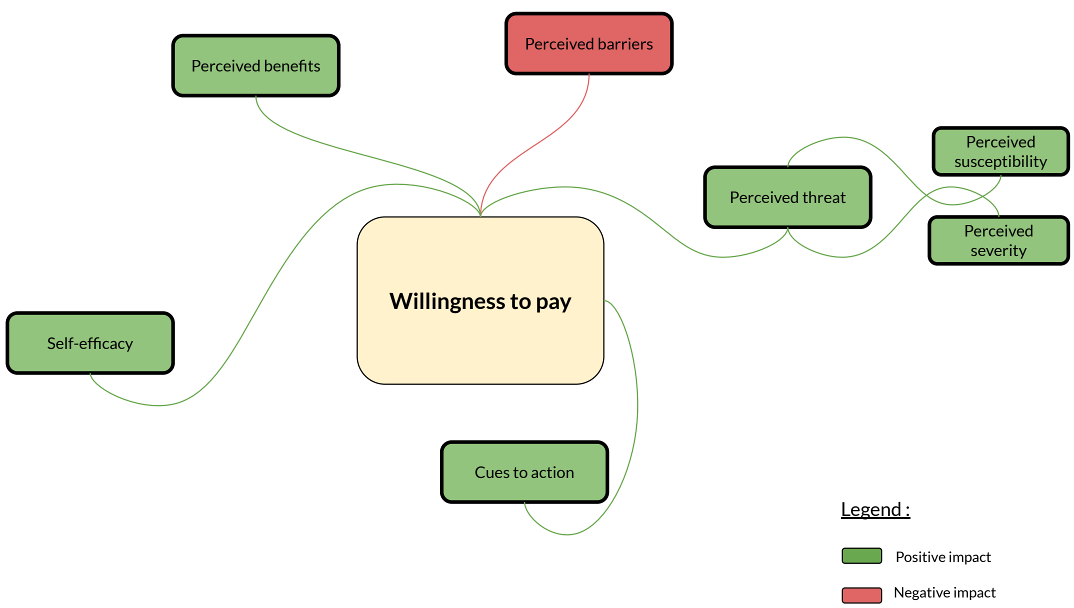
Self-efficacy

The fourth component of the HBM is Self Efficacy (SE), which can be defined as an individual's belief in their ability to succeed in specific situations or tasks (Bandura et al., 1999). In the context of our study, SE refers to an individual's beliefs regarding their ability to contribute to and be involved in a mitigation measure. These beliefs may include factors such as their financial capacity to participate in a project, as well as their capacity to personally engage in the construction and diffusion of the project. It should be noted that these questions were formulated in a manner that aimed to generate positive reinforcement for the individual. As per previous literature, it is anticipated that individuals with a high level of SE, i.e., those who feel capable of contributing to a mitigation policy, will display a greater WTP than those who do not.

Cues to action

The last component of the model are the Cues to action (CA). This component is a bit particular because it does not correspond to individual beliefs but rather to elements that could directly influence the behavior of an individual and therefore his contribution to a cooling strategy project. Thus, in this component, we seek to find elements that could push people to take action. Among these elements, we find financial incentives but also incentives linked to social influence such as the entourage or public influence. Here, it seems more difficult to estimate the impact that CA will have on the WTP of individuals. But again, in the case of HWs, Akompab et al., 2013 found that CA were a good predictor of adaptive behaviours during a HWs.

Figure 2.4: Healh belief model framework



The Figure 2.4 gives us a better understanding of the relationship between the various components of the HBM and the WTP. In this figure, components with a positive effect are shown in green. This means that the higher an individual's level of one of the green components, the higher his or her PT is expected to be.

For example, the higher an individual's WTP, the more he or she perceives the risks of HWs, and therefore the higher his or her ability to contribute to MMs. The mechanism is similar for PBARs in red, however, the more barriers an individual perceives, the lower his WTP will be.

2.2.3 Limitations of the health belief model

Like all fairly simplistic models, the HBM has some limitations. Again, we cannot make an exhaustive list of the biases and limitations of this model. We will limit ourselves to the main ones. First, since the HBM is a psychological model, it does not necessarily take into account the emotional factors of individuals. For example, fear can be considered as an important stimulus in the decision of individuals to take an action (Witte, 1992).

We can also underline that other elements influence the health related behaviors. Janz and Becker, 1984 takes the example of the cigarette or the brushing of teeth which are health behaviors which integrate a component related to the habit. Janz and Becker, 1984 gives other examples of factors or influences not taken into account by the HBM such as the social environment, environmental or economical factors. Indeed, the HBM does not take fully into account behaviors that could be performed for non-health related reasons.

For example, quitting smoking or starting to run can give us a social approval that will be highly valued in the individual's decision making. Moreover, a person living in a very polluted city will be more inclined to contribute to a project aiming at improving the air quality. We can add that the HBM assumes that all individuals have access to the same information about a disease or a hazard, which is not the case in reality. Finally, the HBM assumes that CA are widely used to encourage people to act and that health related action is the main goal in the decions making of individuals [4]. We can nevertheless note that PBARs and CA allow us to integrate a certain form of social influence in our model, allowing us to get closer to a model like the TPB.

2.3 The modifying factors of the health belief model

As discussed, the HBM has certain limitations and does not take into account all the factors that can influence health related behavior. For example, Champion, Skinner, et al., 2008 considers that knowledge and sociodemographic factors are modifying factors that can influence health perceptions. Given that the components of the HBM are presumed to affect individuals' behavior and their WTP, these modifying factors can also impact the HBM and, ultimately, the WTP of individuals.

[4] University of Boston, The Health Belief Model, 2022

2.3.1 Environmental awareness

In this study, to complement the HBM, we wanted to include more information. First, we wanted to obtain information on the respondents' environmental knowledge and opinions. We therefore asked the following questions at the beginning of the questionnaire, before the questions related to the HBM. As with each component of the HBM, the questions were in the form of statements that respondents could answer using a symmetric Likert scale. Since the purpose of these questions was double - knowledge and opinion - it was necessary to find questions that would allow us to address both. To remain consistent, the questions that were asked are all more or less directly related to HWs and the urban environment. Moreover, by asking questions of this type, it should be fairly easy to see whether some respondents are climate sceptics or, on the contrary, whether others are strongly committed. We will discuss this in further detail during the next chapter.

Regarding the impact of this section on the components of the HBM, we can hypothesize that people who are climate sceptics or have less knowledge have a much lower PT than others. It is also possible that they do not perceive as many benefits and see more barriers. Thus, depending on the type of individual, it would seem that this knowledge or opinion on the environment could impacts all the components of the HBM, probably in heterogeneous ways. Thus, if a person is climate sceptic or has little knowledge, his or her WTP for a cooling island to mitigate UHIs might be potentially lower. However, this remains an assumption and we do not have solid proofs to push such conclusions.

2.3.2 Socioeonomic variables

Age and gender playing an exacerbating role

Among the most influential socio-economic variables, gender and age seems to be really significant. In this study, respondents were simply asked to indicate their gender, either male or female, and their age. In terms of age, participants were first asked to select from various age categories, followed by the option to specify their age freely. As briefly mentioned in 1.2.2, elderly individuals are particularly vulnerable to extreme heat. Notably, Fouillet et al., 2006 demonstrated based on the well-documented 2003 HWs in France that mortality rates increased significantly with age, indicating that the older an individual is, the more susceptible they are to mortality due to HWs. However, it is worth noting that this phenomenon may not be observed below a certain age, as found in the study by Fouillet et al., 2006, which set the threshold at 35 years. In terms of gender, the authors discovered that during the 2003 HWs, the mortality ratio was significantly higher among women, at 15%, and the total excess mortality for women was 75% higher than that for men (Fouillet et al., 2006). Consequently, we may expect that age and gender will have a substantial impact on our HBM, especially on PT. This was verified by Akompab et al., 2013, who determined that age was a crucial predictor of risk perception. As for CA, it appears that women are more responsive (Croson & Gneezy, 2009).

However, while elderly individuals may be more susceptible to the harm of an HWs, it is uncertain whether they are more responsive to environmental factors and capable of contributing proportionally to environmental causes. For instance, age could have a negative impact on pro-environmental behaviors (PEBs), as noted by McCluskey et al., 2009 regarding fair trade product consumption. Nevertheless, the matter is not that simple. Indeed, as indicated by Blankenberg and Alhusen, 2019 in their meta-analysis of PEBs, these behaviors tend to follow a specific pattern. Therefore, individuals under the age of thirty and those between 60 and 69 may be more inclined to engage in PEBs, such as paying for a mitigation measure. Finally, regarding gender, numerous studies have consistently reported a gap between genders, with women being more inclined to adopt PEBs Zelezny et al., 2000.

The social status having mixed outcomes

Regarding more social status characteristics, we employed four distinct questions. Initially, we asked whether individuals had completed higher education, and if so, the number of years completed. Next, we asked for households' monthly disposable income by offering different brackets, as well as their SPC, which were established and adapted based on the categories proposed by INSEE[5][6]. An inequality can be observed between the wealthiest individuals who are less exposed to HWs and the least wealthy individuals who are more vulnerable. A very recent study utilized a spatial analysis of a typical summer mid-day observation in Los Angeles to demonstrate the differences in surface temperatures between the poorest and richest neighborhoods in the city of Los Angeles. The findings of this study indicate a significant negative correlation between ground temperatures and median household income across LA County (Yin et al., 2023). This may be attributed to the factors that exacerbate UHI, which we discussed in 1.2.1. These include neighborhoods with low vegetation presence and a prevalence of concrete. Moreover, low-income individuals typically reside in homes with low thermal protection standards, rendering the impact of HWs even more significant (Sakka et al., 2012). Additionally, as we noted in 1.2.2, HWs mortality primarily affects physically weak individuals with poor health, characteristics that are particularly common among the poorest populations. This findings seems plausible since individuals with high income and high socioeconomic status may be less inclined to perceive risks as threatening as poorest populations(Akompab et al., 2013). As a result, we can also hypothesize that individuals with low income may face more PBARs than others due to low income.

Regarding the impact of these factors on PEBs and WTP, the literature suggests that education plays the most

[5] Consulter la PCS 2020
[6] Revenus et patrimoine des ménages

significant role. Generally, individuals with the most years of education are the most informed and engaged. A study on Europeans found a substantial causal effect of education on pro-environmental behavior and provided evidence that education may make individuals more aware of the external effects of their behavior and more concerned with social welfare (Meyer, 2015). These findings appear to be supported by the meta-analysis of Blankenberg and Alhusen, 2019. While education has a greater impact than income on PEBs, individuals with higher incomes still tend to have a higher WTP for some programs such as green electricity (Zorić & Hrovatin, 2012). Concerning SPC, a study by IFEN[7] reveals that the probability of reporting few environmentally friendly practices is 2.35 times higher for farmers, craftsmen, merchants, or business leaders than for employees. Also, workers tend to adopt the least concrete actions. On the other hand, more educated categories such as executives or higher intellectual professions are more likely to engage in concrete actions for the environment. Thus, for our WTP, we can expect that the most educated individuals will participate the most. For income, the effects appear mixed, but we could expect that individuals with the least income would contribute the least.

Household structure

The household structure can be defined as the daily environment of individuals. To establish this environment, we asked respondents if they were in a couple, and if so, what their status was, as well as whether they had children and, if so, how many, and finally, the number of adult persons they lived with. An analysis of the 2003 HWs by Fouillet et al., 2006 indicates that during one of the hottest periods of the HWs, August 1st to 20th, the mortality ratios of single individuals were significantly higher than those of married individuals. Akompab et al., 2013 also found results consistent with this, as married individuals were found to have a lower perceived vulnerability and susceptibility to HWs. Conversely, Akompab et al., 2013 found that individuals who lived with others were more likely to perceive a high risk. Consequently, it is difficult to generalize as the results vary between married individuals and those living with others.

Regarding PEBs, it seems that the conclusions are reversed. According to the meta-analysis of Blankenberg and Alhusen, 2019 citing the works of Clark et al., 2003, Longhi, 2013, and Johnson et al., 2004, the PEBs of individuals is influenced by household structure. However, the size of the household would have a negative impact on PEBs. This could be partly explained by the social practice theory as described in Watson et al., 2012. This result diverges from what Akompab et al., 2013 observed in their studies. Thus, if we were to rank individuals according to their household structure, we could expect that single women would be the individuals with the highest PEBs.

[7] IFEN, L'environnement, de plus en plus intégré dans les gestes et attitudes des Français, janvier-février 2006

Ownership status

In this study, we also wanted to know if owning a property had an impact on the PT of HWs and the WTP of individuals. To do this, we asked respondents to specify if they owned their homes and if they owned an air conditioning device. While Akompab et al., 2013 found that owning a fan had more impact than owning air conditioning, we chose to keep air conditioning. Indeed, as this device is more efficient and expensive, we think it is more relevant. Regarding the literature, we did not find any study that investigated the links between private property and the perception of danger. However, homeowners are generally richer than renters. Therefore, we can assume some similarity between these two variables. Finally, we can the hypothesis that those who own a air conditionning device might have a lower perceived susceptility than other as well as lower PB as they already benefits from their own cooling devices.

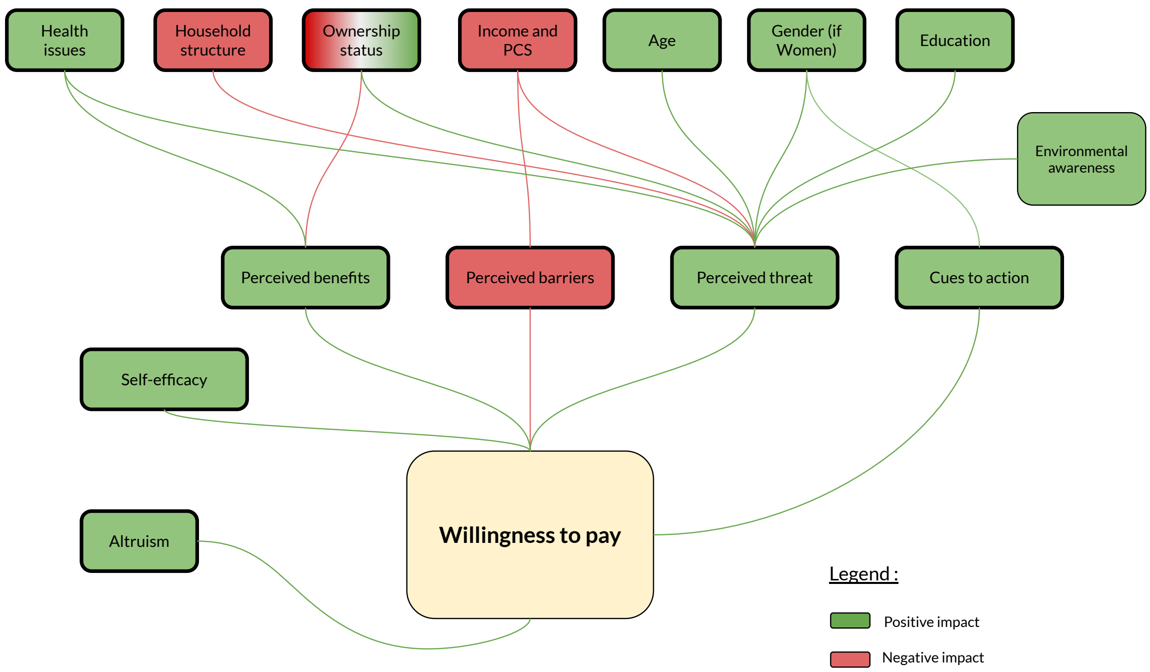
Altruism

To measure altruism and its impact on WTP, we asked respondents if they had ever supported an association, either punctually or regularly. This question seems relevant given our scenario. Thus, we can expect that people who have already supported an association are more familiar with this type of behavior and are more likely to contribute to the project presented. Unfortunately, we cannot rely on scientific literature to estimate the impact that this variable could have. We can only assume that people who have already contributed in the past can be considered altruistic, and therefore, their ability to contribute to a project like the one presented in this study will be greater. However, we cannot affirm anything yet, we will have to wait for the results of the study to see if this question will have played a determining role or not.

History with heat

Finally, our last survey question asked whether respondents had ever experienced heat-related problems in the past. Intuitively, it seems that individuals who have experienced such issues may have a higher PT compared to others. Additionally, it is possible that this question is strongly correlated with the age of individuals. Concerning the impact of this variable on WTP, it is difficult to estimate. We would tend to assume that individuals who have had health problems related to heat in the past would be more likely to contribute. However, this is only an intuition, and it will be interesting to examine the results regarding this variable.

Figure 2.5: Extended health belief model framework



The Figure 2.5 uses the same mechanism as the Figure 2.4, but adds the influence of modifying factors. Here, this figure gives us a better understanding of how socio-economic variables can influence the various components of the HBM and, ultimately, the WTP. For example, the higher an individual's income, the lower his or her level of PBARs, which in turn may lead to a lower WTP.

2.4 Econometrical methods[8]

In the previous sections, we looked at the variables that could be used to assess WTP for an UMF. However, we have not yet looked at the methods that could be used to study this relationship. The aim of this section is to present the method that will be used to investigate the impact of HBM and the modifying factors on WTP. In econometrics, the choice of method depends on the variable to be explained, in this case the WTP. As we discussed in the presentation of our scenario, we have opted for a payment card approach, giving respondents a choice of several WTP levels. We are therefore dealing with a variable that can be considered

[8]This section is drawn from the course on qualitative variables given by Muriel Travers in the Master of Applied Econometrics of the IAE Nantes

categorical. A categorical or qualitative variable is one that takes different modalities, or different levels, as its value. For example, gender is a categorical variable, since it can take either male or female as values. Several methods exist for dealing with categorical variables. The choice of method will differ according to the number of modalities the variable takes. For example, for a two-modality variable such as gender, we'll use logistic or probit regression. On the other hand, for a variable with more than two modalities, we'll use multinomial models.

2.4.1 Introducing the logistic regression

If we've seen so far that our WTP has several modalities, we can group them together to end up with two. We'll see in the next chapter what choice has been made to group this variable. From now on, we'll try to model the probability of our WTP taking the value 1 if the individual responded above a certain threshold, or 0 otherwise (Equ. 2.1).

$$\begin{cases} y_i = 1 \text{ if } y_i^* > c \\ y_i = 0 \text{ if } y_i^* \leq c \end{cases} \tag{2.1}$$

The logit function whose error rates are assumed to follow a logistic distribution can be expressed as follows (Equ. 2.2)

$$\begin{cases} Prob(y_i = 1) = Prob(u_I \leq x_i\beta) = F(x_i\beta) \\ Prob(y_i = 0) = 1 - Prob(u_I \leq x_i\beta) = 1 - F(x_i\beta) \end{cases} \tag{2.2}$$

Where F is the distribution function of a logistic distribution:

$$F(x_i\beta) = \frac{e^{x_i\beta}}{1 + e^{x_i\beta}} \tag{2.3}$$

The coefficients are obtained using the maximum likelihood estimation. We will seek to maximize this maximum likelihood L (Equ. 2.4). The likelihood of an observation is equivalent to the probability of detecting the phenomenon y_i on the basis of the $x_i$values. Our aim is to optimize this L in order to select the model that produces the most likely sample observation, from the range of achievable models. The L is said to be asymptotically efficient. This means it is unbiased (convergent) and has the smallest variance.

$$L(Y,\beta) = \prod_{i=1} F(x_i\beta)^{y_i}(1 - F(x_i\beta))^{1-y_i} \tag{2.4}$$

Unlike the ordinary least squares method utilized for estimating linear models, the coefficients of the logistic regression are not readily interpretable in terms of marginal propensity. The coefficients only indicate the level of significativity as well as the positive or negative influence of variables on the probability. Obtaining the sign of the coefficient will tell us whether the probability of y_i is an increasing or decreasing function of explanatory variables. The first step is to check the influence of the explanatory variables on the variation of the variable to be explained. We perform this test using the likelihood ratio statistic, which can be expressed as follows (Equ. 2.5).

$$2(LL(\beta) - LL(\beta_c)) \rightarrow \chi^2_{1-\alpha}(k) \tag{2.5}$$

Where :

- k is the number of explanatory variables in the estimated (unconstrained) model, excluding the constant
- $LL(\beta)$: value of the log likelihood estimate when the model includes all the model's explanatory variables
- $LL(\beta_c)$: value of the log likelihood estimate when the model contains only the constant

The test is based on the following assumptions :

$$H_0 : \hat{\beta}_1 = 0,..., \hat{\beta}_k = 0$$
$$H_1 : \hat{\beta}_1 \neq 0,..., \hat{\beta}_k \neq 0$$

If the probability associated with $\chi^2_{1-\alpha}(k)$ is lower than 0, the null hypothesis H_0 is rejected at the 5 % risk threshold and the model can be conserved.

Next, we use the Wald test for the significativity of the explanatory variables. The z Wald statistic can be expressed as follows :

$$z = \frac{\hat{\beta}_j^2}{\hat{\sigma}_j^2} \geq \chi^2_{1-\alpha}(1) \tag{2.6}$$

With the following assumptions :

$$H_0 : \beta_j = 0$$
$$H_1 : \beta_J \neq 0$$

If the p-value associated with z is lower than 0.05, we reject the null hypothesis H_0, which indicates the nullity of the estimated coefficient.

When we want to study the impact of a quantitative variable on the probability of y_i, we can use marginal effects. In the context of a logit model, the marginal effect comes as follows (Equ. 2.7). However, when we're looking at the impact of categorical variables, we'd rather study the odd-ratio.

$$\frac{\beta_j e^{x_i\beta}}{(1+e^{x_i\beta})^2} \tag{2.7}$$

Several indicators exist to measure the performance of a Logit model. The most widely used measure is McFadden's R_2. This indicator, ranging from 0 to 1, gives us the model's goodness of fit. The closer this indicator is to 1, the better the model's performance. A well-performing model means one that best explains the variance of the variable under investigation. However, if we wish to compare the performance of several models, we need to use the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The lower the AIC/BIC, the better the model. Finally, to assess the predictive quality of a logit model, we can use the confusion matrix. The higher the sensitivity, accuracy and specificity of this matrix, the better the model. On the other hand, a good model will have low error and false-positive rates.

2.4.2 Introducing the ordered Logistic Regression

As we mentioned earlier when presenting the scenario, we chose to present the WTP in the form of a payment card. The participants had to choose between several mutually exclusive modalities, ordered from the smallest amount to the largest. In this context, it becomes relevant to use an ordered logit regression. We can generalize the dichotomous model seen above as follows (Equ. 2.8). When Y takes j modalities ranging from $j=1$ to k for each individual $i=1,...,$, there are several cut-off values $\alpha_1,...,\alpha k-1$ such that :

$$Y_i = \begin{cases} 1 \text{ if } Y_i^* < \alpha_1 \\ 2 \text{ if } \alpha_1 \le Y_i^* < \alpha_2 \\ ... \\ k \text{ if } Y_i^* \ge \alpha_{k-1} \end{cases} \tag{2.8}$$

Where :

- $\alpha_{j+1} > \alpha_j$.

Thus, the latent variable Y_i^* depends linearly on quantitative or qualitative explanatory variables (Equ. 2.9).

$$Y_i^* = \sum_{m=i}^{p} \beta_m x_{im} + u_i = X_i\beta + \varepsilon_i \qquad i=1,...,n \tag{2.9}$$

We therefore have the probabilities of the different j modalities depending on the estimated coefficients of the explanatory variables and the constants associated with each level of Y. Let's consider a model with Y taking three ordered modalities with 1< 2< 3 (Equ. 2.10). We would have :

$$\begin{cases} Prob(Y_i = 1|X_i, \beta, \alpha) = Prob(X_i\beta + \varepsilon < \alpha_1) = Prob(\varepsilon_i < \alpha_1 - X_i\beta) = P_{i1} \\ Prob(Y_i = 2|X_i, \beta, \alpha) = Prob(\alpha \leq X_i\beta + \varepsilon < \alpha_2) = Prob(\alpha_1 - X_i\beta \leq \varepsilon_i < \alpha_2 - X_i\beta) = P_{i2} \\ Prob(Y_i = 3|X_i, \beta, \alpha) = Prob(X_i\beta + \varepsilon \leq \alpha_2) = Prob(\varepsilon_i \geq \alpha_2 - X_i\beta) = P_{i3} = 1 - P_{i1} - P_{i2} \end{cases} \tag{2.10}$$

The likelihood of each i^e observation is given by (Equ. 2.11).

$$L_i = P_{i1}^{\delta i1} \times P_{i2}^{\delta i2} \times (1 - P_{i1} - P_{i2})^{1-\delta i1-\delta i2} \tag{2.11}$$

If :

- $\delta_{i1} = 1$ if $Y_i = 1$ and 0 otherwise.
- $\delta_{i2} = 1$ if $Y_i = 2$ and 0 otherwise.

The estimated model coefficients are then obtained by maximizing the maximum likelihood estimate (Equ. 2.12)

$$\max_{\alpha\beta} \sum_{i=1}^{n} LogL_i \tag{2.12}$$

The primary assumption is the proportional odds assumption, also known as the parallel lines assumption. This supposition states that the influence of predictor variables - like the components of the HBM - on the odds of being in a higher outcome category of WTP is consistent across all shifts from one category to another. This means that, whatever the modality j considered, an explanatory variable has the same influence on $P(Y \leq j/X = x)$ and therefore on the probability of $P(Y > j/X = x)$. Consequently, when the value of the explanatory variable increases by one unit, we have (Equ. 2.13)

$$\frac{Prob(Y \leq j/x)/Prob(Y > j/x)}{Prob(Y \leq j/x^{'})/Prob(Y > j/x^{'})} = \frac{e^{\hat{\alpha_1} + x\hat{\beta_1}}}{e^{\hat{\alpha_1}} + x^{\hat{'}}\beta_1} = e^{\hat{\beta}_1} \tag{2.13}$$

Chapter 3

Statistical and econometrical results

As observed in the previous chapter, the various methodologies employed necessitate the utilization of a questionnaire. In order to design our questionnaire, we used the survey tool provided by our institution, the University of Nantes. This decision was motivated by the platform's capability to facilitate the creation of questionnaires. Additionally, employing this platform ensures that our data remains securely stored within the borders of France.The online diffusion of this questionnaire extanded from April 22 to May 17, 2023. The authors shared the questionnaire via their social networks, unfortunately, the questionnaire was not distributed as widely as the authors would have liked. Consequently, a total of 70 responses were obtained. This chapter will be dedicated to the processing and analysis of these collected responses.

3.1 Descriptive analysis

3.1.1 Sample overview

As mentioned in the introduction, our questionnaire received 70 responses. However, some of these responses were not usable for our survey. Indeed, 15 people did not complete the entire questionnaire. Several factors may explain this delay in the survey. Among the elements that could play a role, there is the time that the survey takes. Indeed, if the questionnaire is too long and the questions are too complex or disturbing, this can lead to cognitive fatigue among the respondents. Thus, we wanted to know the average response time. According to LimeSurvey data, the average time for our questionnaire was about 10 minutes. If we cannot know the precise reasons for these drop-outs, it would be surprising if this was due to the length of the questionnaire, since it is still relatively short. Then, we removed people who did not live or work in Nantes. Indeed, the first two questions of our survey asked if people lived or worked in Nantes. If people answered *No* to both questions, they were directly sent back to the end of the questionnaire. Among the 70 people, 12 could not meet these conditions. We therefore ended up with a sample of 43 people. Then we had to remove the people who did not want to answer or did not know what to answer to the WTP. Only two people did not want to answer this question, but several of the people who answered 0 were considered to be protest zeros based on their answers. We will discuss these protest zeros in more detail later in the chapter. In the meantime, we can begin our analysis with a sample of 32 individuals.

3.1.2 Descriptive statistics

Socioeconomic variables

Table 3.1 presents an overview of the socio-economic characteristics observed within our study population. To enhance comprehensibility and readability, we have consolidated certain modalities based on the core questionnaire. In terms of gender distribution, nearly 60% of the population under investigation identifies as female. Regarding age, it is evident that our sample predominantly comprises individuals in the younger age bracket, with approximately one-fourth of the population being under 22 years old and almost 60% falling below 32 years old. Notably, this indicates a lower median age compared to the general population of Nantes, where only 29.6% falls below the age of 32, suggesting a relatively youthful structure of our sample[1].

In terms of educational level, our sample demonstrates a significant level of qualification, with one-fourth of the population having completed at least six years of education, and a more general trend indicating that 60% have completed a minimum of four years of education (Table 3.1). If we look a little more closely at the educational levels, it becomes apparent that a majority of individuals holding a master's degree (4-5) are found within the younger age groups (Figure 6.1). Consequently, it can be assumed that a large portion of our population is either still engaged in studies or has recently entered the labor market. This observation is confirmed by the SPC of our respondents, which indicate that half of the population remains enrolled as students. Conversely, individuals with a higher level of qualification - nine years or more - are predominantly found in older age groups (Figure 6.1 Appendix). Lastly, it is worth noting that individuals with no formal education are exclusively men belonging to the 58 to 62 age group. After comparison of these findings with data from INSEE, it becomes evident that our sample exhibits a higher level of qualification than the average population in Nantes. Indeed, in Nantes, about half of the population has a higher education degree[2].

Returning to the SPC, we observe that more than a third of our sample consists of active individuals, while around 12.5% are classified as *inactive* (including unemployed or retired individuals) (Table 3.1). Originally, this variable accounted for all the occupational categories listed by INSEE. However, based on our findings, it seemed more appropriate to group together individuals who were employed. The significant presence of

[1] Dossier complet, Commune de Nantes (44109)
[2] *ibid*

students in our sample is reflected in the income statistics, with approximately 35% of respondents earning less than 1000 euros.

As for the status and situation of our individuals, 43% of them are single and 57% are in couples (Table 3.1). The majority of those in couples are in free unions, which can probably be explained by the fact that our population is very young. On the scale of Nantes, 40% of the individuals are single. In contrast, people in couples are more often married (30%), unlike our sample[3].

Regarding housing, 65% live in an apartment (Table 3.1). At first glance, one might say that this is characteristic of a young and student population. Nonetheless, we must keep in mind that Nantes is a large city and that on the scale of its population, 77% of people live in apartments[4]. Therefore, this relatively low figure might seem surprising. Next, we observe that 37.5% of our population is a homeowner. This figure is pretty much the same as that observed by INSEE on the inhabitants of the Nantes metropole.

As far as the housing structure of our population is concerned, it seems to be a little more balanced since 40% of the population lives alone (Table 3.1). The rest live with two or more people. With respect to children, our results indicate that only one person lives with children. Thus, we decided not to include the variable in the study.

When we asked if individuals had ever donated to an association, 81.2% said yes (Table 3.1). Regarding air conditioning, sadly for our study (but fortunately for GHG emissions) no one has an air conditioning system. Finally, regarding health, almost 10% of our sample has already had issues with heat.

[3] *ibid*
[4] *ibid*

Table 3.1: Socioeconomic caracteristics

Variable	Values	N
Gender	Female	59.4%
	Male	40.6%
Age	18-22	25.0%
	23-32	34.4%
	38-57	25.0%
	58-77	15.6%
Education	0	12.5%
	1-3	28.1%
	4-5	34.4%
	6 and more	25.0%
Income	Less than 1000	34.4%
	1000-2000	31.2%
	2000-3500	21.9%
	More than 3500	12.5%
SPCs	Active	37.5%
	Students	50.0%
	Inactive	12.5%
Status	Single	43%
	Married	15.6%
	Pacsed	6.2%
	Free union	31.2%
Property	Apartment	65.6%
	House	34.4%
Owner	Yes	37.5%
	No	62.5%
Living	Alone	40.6%
	Two	46.9%
	More than two	12.5%
Altruism	Never	18.8%
	Yes	81.2%
Health issue	Never	90.6%
	Yes	9.4%

The willingness to pay

The Table 3.2 gives us the cross statistics between WTP, gender and age of individuals. As our sample is small, the analysis is less interesting but we can already see that the interest of the residents becomes smaller from the sum of 50 Euros (Table 3.2) . We also notice that no one chose the last two highest brackets. The most represented WTP range in the sample is 10-20, with 12 individuals (37.5% of the sample) (Table 3.2). In this range, two-thirds are female. The 18-22 age group makes up 17% of this bracket, while the 38-57 group constitutes the largest proportion at 42% (Table 3.2). The 60-70 and 70-80 WTP categories each include a single individual (3.1%), both being female. One is in the 23-32 age group (for the 60-70 WTP), and the other is in the 58-77 age bracket (for the 70-80 WTP)(Table 3.2). The 20-30 WTP range comprises 6 individuals (18.8%) (Table 3.2). Here, the gender split is the same as the 10-20 range, but there's a significant shift in age distribution. The majority (67%) belong to the 23-32 age group (Table 3.2). This shift in age distribution might be explain by an increase in income. To summarize, the majority of individuals fall within the 10-30 WTP range, with the 38-57 age group being the most prominent across the categories. Females generally demonstrate a higher WTP in lower and higher categories, while males are more represented in the middle categories.

Table 3.2: Distribution of the willingness to pay

		Gender		**Age**			
		Femme	**Homme**	**18-22**	**23-32**	**38-57**	**58-77**
WTP	**N**	**N (%)**		**N (%)**			
0	1 (3.1%)	0.00	**100**	0.00	0.00	0.00	**100**
0-10	4 (12.5%	**75**	25	**50**	0.00	**50**	0.00
10-20	**12 (37.5%)**	**67**	33	**17**	25	**42**	17
20-30	6 (18.8%)	**67**	33	**17**	**67**	**17**	0.00
30-40	2 (6.2%)	50	50	**50**	**50**	0.00	0.00
40-50	4 (12.5%)	25	**75**	**25**	50	0.00	**0.25**
50-60	1 (3.1%)	0.00	**100**	**100**	0.00	0.00	0.00
60-70	(3.1%)	**100**	0.00	0.00	**100**	0.00	0.00
70-80	(3.1%)	**100**	0.00	0.00	0.00	0.00	**100**

As mentioned above, a number of individuals who answered 0 to the WTP could be considered as protest zeros. Indeed, once an individual answered 0 to the WTP, a new question was presented to him asking him why he had made this choice. An individual will be considered a protest zero if he or she disagrees with some aspect of the hypothetical scenario presented. Table 6.2 in Appendix gives us the different possible answers. Among these answers, some can be considered as protest answers, it is the case for the following answers :

- *Estime que le financement devrait être pris en charge par les pouvoirs publics*
- *Manque d'information sur le projet*
- *Pas convaincu(e) de l'efficacité des micro-forêts de Miyawaki*

In order to avoid bias, we preferred to remove these protest zeros from the study. This is the reason why we end up with only one zero instead of 10. We also note that one person used the other option to tell us that he was already too heavily taxed as a single person (Table 6.2).

Environmental awareness

The Table 3.3 presents survey responses to environmental statements. In general, respondents demonstrate a high degree of environmental awareness and appear to support aggressive measures to address climate change and environmental degradation. For instance, they attribute climate change primarily to human activities (71.9% strongly disagree with statement 1, which implies the opposite), and they favor measures like restricting petrol and diesel vehicles in urban centers (53.1% strongly disagree with statement 2 suggesting that such a measure is excessive) (Table 3.3). Moreover, there is a significant disagreement (56.2% strongly disagree) with the statement that actions to combat climate change could harm economic growth (statement 3), indicating a recognition of the potential compatibility between environmental protection and economic growth (Table 3.3).

Table 3.3: Summary of statements: Environmental awareness

			Likert scale (%)				
Composantes	**N**	**Statement**	**SD**	**D**	**N**	**A**	**SA**
Environmental awareness	1	La hausse des températures mondiales est principalement due à des variations naturelles du climat plutôt qu'aux activités humaines	71.9	25.0	-	3.1	-
	2	L'interdiction des véhicules à essence et diesel dans les centres-villes est une mesure excessive pour lutter contre la pollution de l'air.	53.1	34.4	-	12.5	-
	3	Les efforts pour lutter contre le réchauffement climatique pourraient nuire à la croissance économique et à la création d'emplois	56.2	28.1	9.4	6.2	-
	4	Les canicules ne sont pas un problème majeur dans les villes et ne nécessitent pas d'actions spécifiques pour les atténuer	81.2	15.6	3.1	-	-
	5	Les entreprises et les gouvernements devraient se concentrer davantage sur l'adaptation aux impacts du changement climatique plutôt que sur la réduction des émissions de gaz à effet de serre.	37.5	34.4	15.6	3.1	9.4
	6	Le développement des transports en commun et des pistes cyclables n'est pas une priorité pour l'amélioration de la qualité de vie en ville.	75.0	15.6	3.1	3.1	3.1
	7	Les actions de reforestation et de restauration des écosystèmes naturels ne sont pas essentielles pour lutter contre le réchauffement climatique et préserver la biodiversité.	81.2	18.8	-	-	-

Summary of statements: Perceived threat

Table 3.4 gives us the results of the statements from the first component of the HBM, PT. As mentioned in the previous chapter, PT can be decomposed into two sub-components.

On Perceived Susceptibility, many respondents express awareness and concern towards HWs. The majority of participants consider that their living conditions increase their vulnerability to HWs (Table 3.4). Moreover, the data reveals the respondents' beliefs that their outdoor activities are significantly influenced by heat, and that the effects of HWs are intensified by climate change. Respondents also consider urban infrastructure, specifically in Nantes, as a factor that could influence vulnerability to HWs.

As for Perceived Severity, the respondents show high levels of concern about the health implications of prolonged heat exposure. Many acknowledge the risks of serious health effects, such as skin cancer, damaged cognitive and physical abilities, dehydration symptoms, and even loss of consciousness (Table 3.4). A significant number also express a willingness to modify their behaviors to avoid heat-related health risks, like staying indoors during a HWs episode. However, the responses vary more when it comes to medical consultation for heat-related symptoms and the potential for heat-related mental health issues.

Despite the significant consensus in responses, some statements, particularly those on lifestyle impact and perceived health risks, show a broader range of opinions, suggesting nuances in the respondents' opinions.

Table 3.4: Summary of statements: Perceived threat

		Statement	Likert scale (%)				
Composantes	**N**	**Perceived Susceptibility**	**SD**	**D**	**N**	**A**	**SA**
Perceived Threat	1	Par rapport aux autres personnes de mon âge, je me considère comme étant plus vulnérable face à la chaleur.	25	40.6	18.8	9.4	6.2
	2	Je considère que les conditions de mon logement me rendent plus vulnérable aux canicules (ex : absence de climatisation, mauvaise isolation, etc.).	15.6	34.4	9.4	34.4	6.2
	3	Je pense que le réseau de santé de ma région est capable de faire face aux problèmes de santé liés aux canicules.	15.6	37.5	28.1	18.8	-
	4	La chaleur a un impact important sur mon choix d'activités en plein air pendant l'été.	-	6.2	3.1	53.1	37.5
	5	L'intensité des canicules est amplifiée par le changement climatique.	-	-	-	21.9	78.1
	6	La fréquence des canicules est amplifiée par le changement climatique.	-	-	-	21.9	78.1
	7	Je pense que la qualité de l'infrastructure urbaine de Nantes peut influencer la vulnérabilité face aux canicules (ex : manque d'espaces verts, surfaces imperméables, etc.).	-	3.1	-	46.9	50
	8	Mon mode de vie et mes activités quotidiennes me rendent plus susceptible d'être affecté par une canicule.	15.6	28.1	6.2	43.8	6.2
		Perceived Severity					
	9	Une exposition prolongée au soleil pourrait augmenter les risques que je développe un cancer de la peau.	-	6.2	-	34.4	59.4
	10	Une exposition prolongée à de fortes chaleurs risque d'altérer grandement mes capacités physiques/intellectuelles au point de ne plus pouvoir travailler.	-	25.0	12.5	31.2	31.2
	11	Si je suis déshydraté(e) pendant une période prolongée, je risque d'avoir des maux de tête et des vomissements.	-	6.2	-	28.1	65.6
	12	Si je suis exposé(e) à des températures élevées pendant une période prolongée, je risque de perdre connaissance.	3.1	12.5	3.1	46.9	34.4
	13	Je pourrais éviter de sortir dans les rues de la ville pendant une vague de chaleur pour éviter les risques pour ma santé.	6.2	15.6	9.4	34.4	34.4
	14	Si je ressens des symptômes tels que des crampes musculaires ou des étourdissements pendant une vague de chaleur, j'irais consulter un médecin immédiatement.	18.8	43.8	9.4	18.8	9.4
	15	Les canicules peuvent me causer des problèmes de santé mentale, comme l'anxiété ou la dépression, en raison du stress lié à la chaleur.	28.1	15.6	12.5	28.1	15.6
	16	Je pense que les effets des canicules sur ma santé peuvent être irréversibles.	6.2	28.1	21.9	34.4	9.4

Perceived benefits

Regarding the PB of MMs, there seemed to be a pronounced tendency towards agreement or strong agreement across all statements, with no one strongly disagreeing on any point. The consensus highlights the respondents' positive perceptions of the potential benefits of cooling strategies to mitigate UHIs. The aspects evaluated include their impact on comfort during HWs, reduction of reliance on air conditioning, lower ambient temperature, and contribution to the aesthetic improvement of neighborhoods and enhancement of air quality. We can notice that 50% of the sample strongly agree with the fact that MMs could reduce their reliance on air conditionning while none of them own a air conditionning system (Table 3.5). Additionally, respondents seems to see value in supporting local and sustainable projects like this, suggesting that they might feel a sense of community.

Table 3.5: Summary of statements: Perceived benefits

			Likert scale (%)				
Composantes	**N**	**Statement**	**SD**	**D**	**N**	**A**	**SA**
Perceived benefits	1	Les îlots de fraîcheur sont essentiels pour améliorer mon confort pendant les périodes de canicule.	-	3.1	-	53.1	40.6
	2	Les îlots de fraîcheur pourraient réduire ma dépendance à la climatisation pendant les canicules.	-	9.4	12.5	28.1	50.0
	3	Les îlots de fraîcheur ont un impact significatif sur la réduction de la température ambiante dans mon quartier.	-	-	25.0	31.2	43.8
	4	Les îlots de fraîcheur pourraient contribuer à améliorer l'esthétique de mon quartier et rendre les espaces publics plus accueillants et agréables.	-	-	3.1	31.2	65.6
	5	Les îlots de fraîcheur pourraient améliorer la qualité de l'air dans mon quartier, ce qui serait bénéfique pour ma santé.	-	-	-	40.6	59.4
	6	Le fait de soutenir un projet local et durable pourrait me donner un sentiment de fierté.	-	3.1	3.1	56.2	37.5

Perceived barriers

Contrasting to the previous table on PB, there is a more varied distribution of opinions on perceived barriers (PBAR), suggesting that while respondents see the potential advantages of cooling strategies, they also acknowledge potential obstacles. The most significant PBAR, are the statement 5 and 7 (Table 3.6). Both of these barriers relate to the ability of individuals to evaluate the potential benefits of cooling strategie.

The respondents are generally convinced about the effectiveness of MMs in combating UHIs, with a high proportion of them disagreeing or strongly disagreeing with the statement 1 (Table 3.6). Some concerns about technical difficulties in setting up and maintaining such structures and potential financial constraints also emerge from the responses.

However, fear of negative judgement from peers if they do not support a mtitigation measure does not seem to be a major barrier, with a majority of respondents disagreeing or strongly disagreeing (Table 3.6). Overall, while there is significant recognition of the potential benefits of cooling strategies, there is also awareness and concern about various possible challenges in implementing such projects.

Table 3.6: Summary of statements: Perceived barriers

Composantes	N	Statement	Likert scale (%) SD	D	N	A	SA
Perceived barriers	1	Les îlots de fraîcheur ne sont pas une solution efficace pour lutter contre les îlots de chaleur urbains.	46.9	37.5	12.5	3.1	-
	2	Je ne dispose pas des moyens financiers nécessaires pour soutenir un tel projet.	9.4	28.1	31.2	28.1	3.1
	3	Mon entourage pourrait me juger négativement si je ne soutiens pas un projet d'îlots de fraîcheur.	28.1	31.2	31.2	9.4	-
	4	Il pourrait y avoir des difficultés techniques liées à la mise en place et à l'entretien des îlots de fraîcheur.	15.6	34.4	37.5	9.4	3.1
	5	Les habitants du quartier pourraient ne pas être informés ou conscients de l'existence et des avantages potentiels des îlots de fraîcheur.	6.2	21.9	9.4	40.6	21.9
	6	Les habitants du quartier pourraient être préoccupés par les possibles nuisances sonores ou visuelles liées à la mise en place des îlots de fraîcheur.	18.8	37.5	28.1	9.4	6.2
	7	Je ne me sens pas assez informé(e) ou compétent pour évaluer l'impact réel des îlots de fraîcheur sur mon environnement.	15.6	34.4	-	34.4	15.6
	8	Je pense qu'il serait plus judicieux d'investir dans des solutions de climatisation intérieure plutôt que dans des îlots de fraîcheur.	87.5	12.5	-	-	-

Self-efficacy

The Table 3.7 reveals a generally positive perception of SE among respondents. Many of the respondents feel confident in their ability to actively participate in collective projects for the establishment and maintenance of MMs in their neighborhood, with the majority agreeing or strongly agreeing with this sentiment.

Likewise, a large proportion of respondents also feel capable of convincing their surroundings to support the cooling strategies, demonstrating a perceived influence over their social circles (Table 3.7).

When it comes to financial contributions, respondents also express a high degree of confidence in their ability to financially contribute to the implementation of cooling strategies in their neighborhood (Table 3.7). Moreover, a significant number of respondents are willing to financially support the creation of cool strategies in other neighborhoods, even if this does not directly benefit their own neighborhood.

Table 3.7: Summary of statements: Self-efficacy

Composantes	N	Statement	Likert scale (%) SD	D	N	A	SA
Self-efficacy	1	Je me sens capable de m'impliquer activement dans des projets collectifs pour soutenir la création et l'entretien d'îlots de fraîcheur dans mon quartier.	-	25.0	21.9	46.9	6.2
	2	Je me sens capable de convaincre mon entourage de soutenir le projet d'îlots de fraîcheur.	-	12.5	9.4	50.0	28.1
	3	Je me sens capable de contribuer financièrement à la mise en place d'îlots de fraîcheur dans mon quartier.	6.2	12.5	21.9	50.0	9.4
	4	Je suis prêt à soutenir financièrement la création d'îlots de fraîcheur dans d'autres quartiers, même si cela ne profite pas directement à mon propre quartier.	6.2	15.6	28.1	40.6	9.4

Cues to action

The Table 3.8 indicates that social influence plays a notable role in respondents' motivations. The majority of participants would be more motivated to engage in a MMs project if they knew that people in their circle were also participating.

The idea of financial incentives also seems to be a significant motivator for the respondents as a large majority of participants agreed or strongly agreed that they would be more inclined to invest if governmental financial incentives were available (Table 3.8).

Medical advice is considered another CA. About 40% of the respondents would be more likely to participate if their doctor talked to them about this initiative, highlighting the role of trusted health professionals in promoting such initiatives (Table 3.8). Endorsements by celebrities or public entities appear to be less influential. Around 25% of the respondents agree that they would be more interested in engaging in MMs projects if these entities were to support and promote them.

Finally, the role of social media campaigns in promoting involvement in the implementation of cooling strategies is considerable. More than half of the respondents agree that they would be more likely to get involved if they encountered awareness campaigns on social media (Table 3.8). These high numbers may be explained by the fact that our population is very youthful and uses social media frequently.

Table 3.8: Summary of statements: Cues to action

			Likert scale (%)				
Composantes	**N**	**Statement**	**SD**	**D**	**N**	**A**	**SA**
Cues to action	1	Je serais davantage motivé(e) à m'engager dans un projet d'îlot de fraîcheur dans mon quartier si je savais que des personnes de mon entourage y participaient aussi.	6.2	18.8	15.6	37.5	21.9
	2	Des incitations financières gouvernementales pour soutenir les projets durables augmenteraient ma motivation à investir dans ces projets.	3.1	6.2	15.6	31.2	43.8
	3	Si mon médecin me parlait de cette initiative, je serais plus enclin(e) à y participer.	6.2	21.9	31.2	34.4	6.2
	4	Si des célébrités ou des personnalités publiques soutenaient et promouvaient les îlots de fraîcheur, je serais plus intéressé(e) à m'engager dans de tels projets.	15.6	25.0	34.4	15.6	9.4
	5	Si je voyais des campagnes de sensibilisation sur les réseaux sociaux, je serais plus susceptible de m'impliquer dans la création d'îlots de fraîcheur.	9.4	15.6	21.9	40.6	12.5

3.2 Hierarchical Clustering on Principal Components

In the previous section, we explored the descriptive statistics of our variables. These statistics provided a general overview of the characteristics and opinions within our population. However, to investigate more deeply into the relationships between different opinions and choices, we need to examine correlations among variables. Specifically, we aim to determine whether certain variables and statements are related to each other. The underlying objective is to identify distinct groups of individuals with similar characteristics, enabling us to study how the components of the HBM influence the WTP of respondants for MMs. To do so, we will use the Hieratchical Clustering on Principle components (HCPC) method. This method consists in creating clusters of individuals from latent variables generated by a Multiple correspondance analysis (MCA). This method is particularly suitable for questionnaires containing categorical variables[5](Husson et al., 2010)

3.2.1 Mulitple Correspondence Analysis

To investigate the potential connections between the different questions within each component, we can employ a statistical technique called MCA. MCA is a useful tool for exploring complex and multidimensional data. Its primary objective is to identify relationships and patterns among several categorical variables. In simpler terms, MCA helps to simplify complex data, leading to improved comprehension and visualization. Given that our study involves multiple categorical variables within each component of the HBM, MCA is a relevant framework.

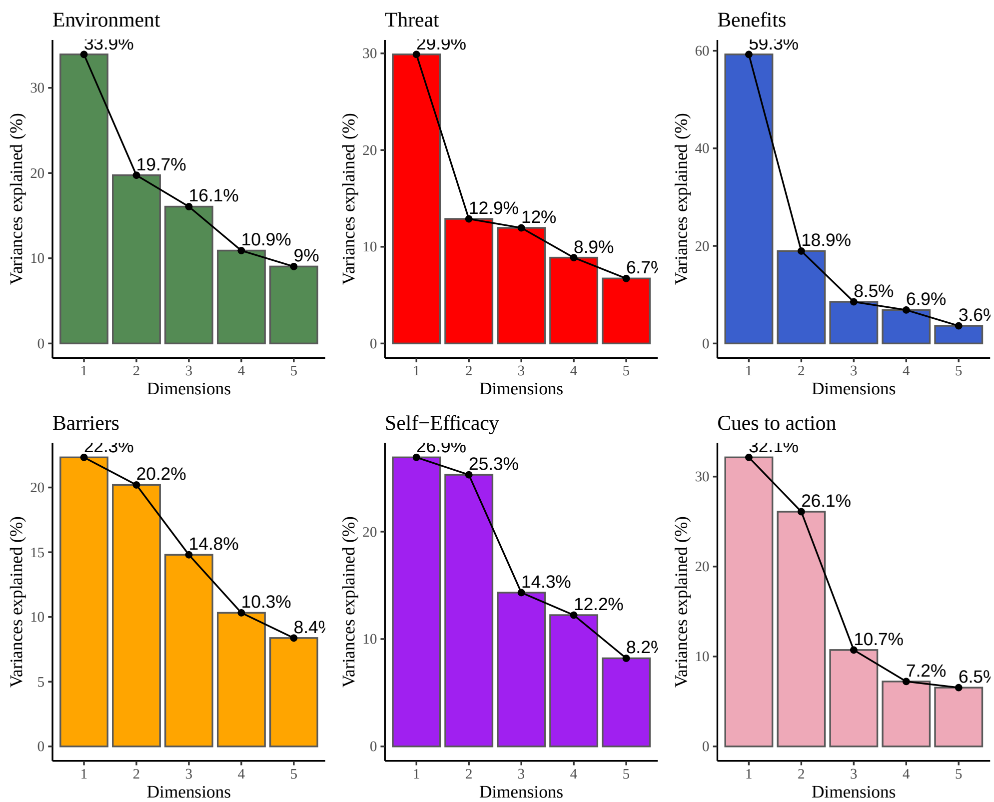
Before applying the MCA to our data, it is important to know that this method is sensitive to small populations. Thus, it is preferable to group certain modalities in case they are not well represented. Based on the tables studied in the previous section, a regrouping of modalities was possible. All the regroupings are available in section 6.1.2 of the Appendix.

As mentioned previously, the objective of the Multiple Correspondence Analysis (MCA) is to simplify our dataset. Initially, without processing, each statement of our components would be represented on 4 different axes or dimensions (5 modalities minus one). Thus, analyzing intra and inter component relationships would be time consuming and complex as it would require looking at dozens of dimensions. By using the MCA on our dataset, it allows us to concentrate all the statements of a component on a new system of axes regrouping a very large part of the inertia (i.e. the variance) in very few axes (or dimensions). Figure 3.1 gives us the inertia of the dimensions associated with each variable.

[5]Multiple modalities

According to the theory, we notice that the majority of the inertia is concentrated on the first axes. Indeed, we observe that all the components exhibit explained variances greater than 70% on the first 5 axes. Figure 3.1 also shows that the first dimension of each component has a higher inertia than the following one. This information leads us to interpret the first factorial design as a priority. In this first design, composed of axes 1 and 2, we always have at least 40% of explained inertia. Therefore, for each component, we will rely on the graphical representation of the first two axes in order to determine potential correlations, similarities between modalities.

Figure 3.1: Barplot of inertia

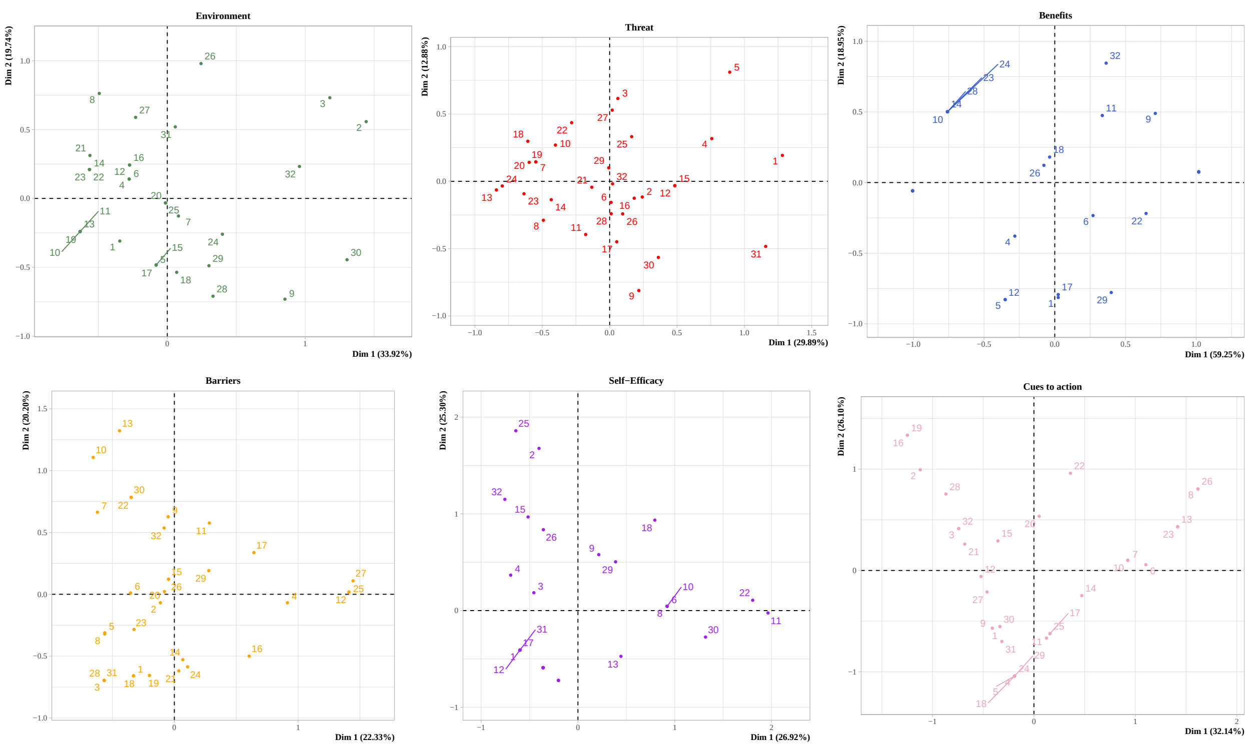


Review of individuals

During an MCA, the first thing to analyze is the general appearance of the individual scatter plot. The individual scatter plot gives us the distribution of individuals on a two-dimensional plan according to their responses. The graphs of individuals are represented by the Figure 3.2. For the PT, the cloud of individuals seems homogeneous, thus, we can't yet make any assumptions about the distribution of individuals. As far as the PB are concerned, the individuals are quite far from the barycentre, so the dispersion of individuals seems quite high.

The clouds of individuals for the last three components look a little like a parabola (Figure 3.2). This parabola is characteristic of a well-known effect in data analysis, the Guttman effect. The appearance of a Guttman effect is more likely when analyzing variables with an uneven number of modalities and a median modality, which is the case in our study following the regrouping of modalities. This effect leads to an opposition between extreme modalities on one axis and an opposition between median and extreme values on the other axis (Chanvril, 2008). The analysis of the modalities will enable us to determine whether this effect is indeed present.

Figure 3.2: Scatter plot of individual



Analysis of modalities

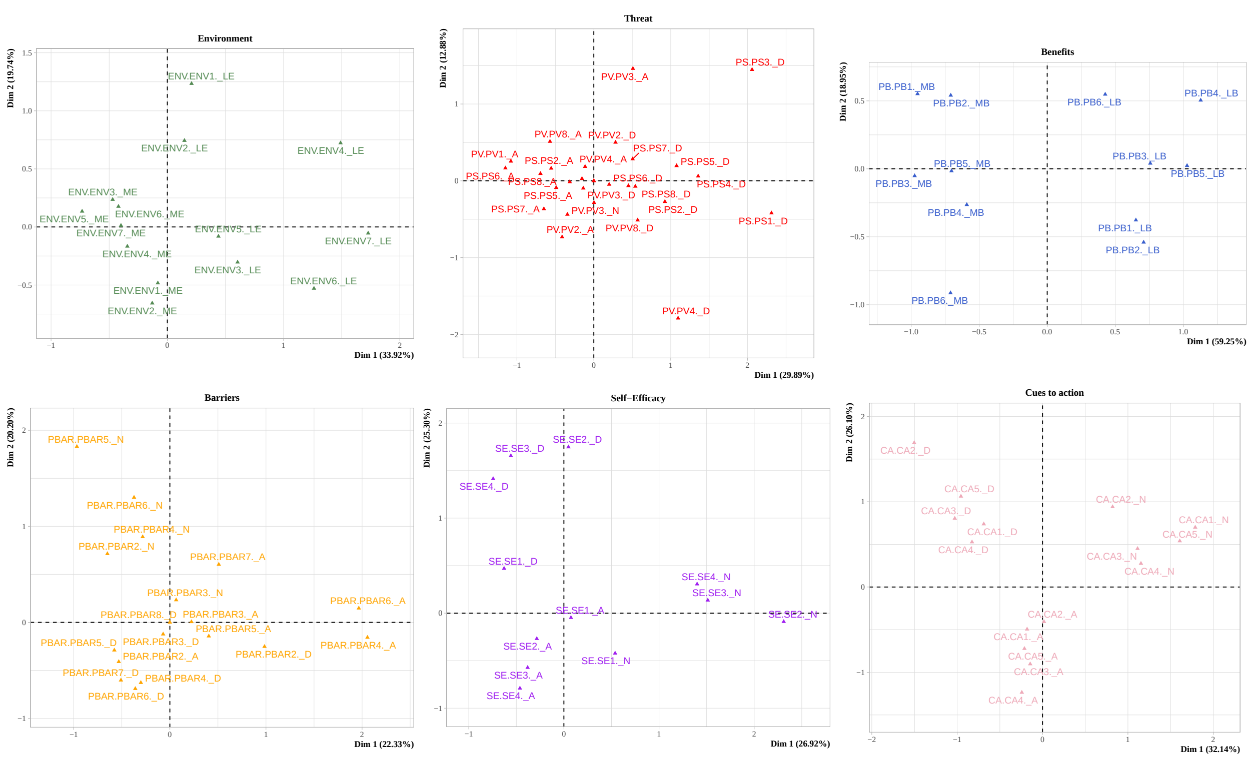
Now that we've studied the individuals, we can continue with the analysis of the modalities. Figure 3.3 gives us the modalities of each components on a two-dimensional plane. The idea here is not to go into detail in the interpretation of each modality and each component but rather to try to establish more general correlations, both between modalities and components.

For the particular case of environmental awareness, most engaged are represented by ME and less engaged by LE. We can notice that ME are mostly located to the left of the vertical axis (Figure 3.3). This vertical axis, which we will call Axis 2, separates ME from LE.The further to the right of the horizontal axis, Axis

1, the less engaged individuals become in their responses regarding environmental statements. We observe a similar pattern for PB, with axis 2 clearly separating those who receive the most benefits (MB) from those who perceive less (LB). Thus, the more we shift to the right of the horizontal axis, the less individuals perceive the benefits of a MMs. The same phenomenon can be observed for PT. Indeed, the majority of responses agreeing with the statements (A) are to the left of the vertical axis, indicating that the further to the right of the horizontal axis one moves, the lower is the perception threat regarding HWs.

For the last three components, we do indeed observe the Guttman effect for SE and CA. For both components, extreme values (D and A) are separated by the horizontal axis (Figure 3.3). On the other side, we have the median value (N), which is opposed by the vertical axis to the two extreme values. In other words, for these two components, the higher you move up the vertical axis, the lower the level of SE and CA, and vice versa. Moreover, the more we move to the right of the horizontal axis, the more neutral the answers are. For PBAR, the Gutmann effect is less obvious. Indeed, the separation between the three modalities is less clear. However, the more we move to the right of the horizontal axis, the more individuals perceive barriers to the implementation of a cooling strategies to mitigate UHIs, and vice versa. On the vertical axis, the more you move up on this axis, the more neutral the individuals' responses are.

Figure 3.3: MCA factor map



3.2.2 Classification

The use of the MCA for a HCPC has enabled us to concentrate much of the information in the first principal components and eliminate noise from the data (Husson et al., 2010). Therefore, the use of MCA will theoretically enable us to have a more stable classification. Classifying refers to forming classes from a set of data. These classes can be defined as sets of individuals sharing common traits or characteristics. To perform our classification, we'll use the `FactoMineR` package (Lê et al., 2008).

Hierarchical trees

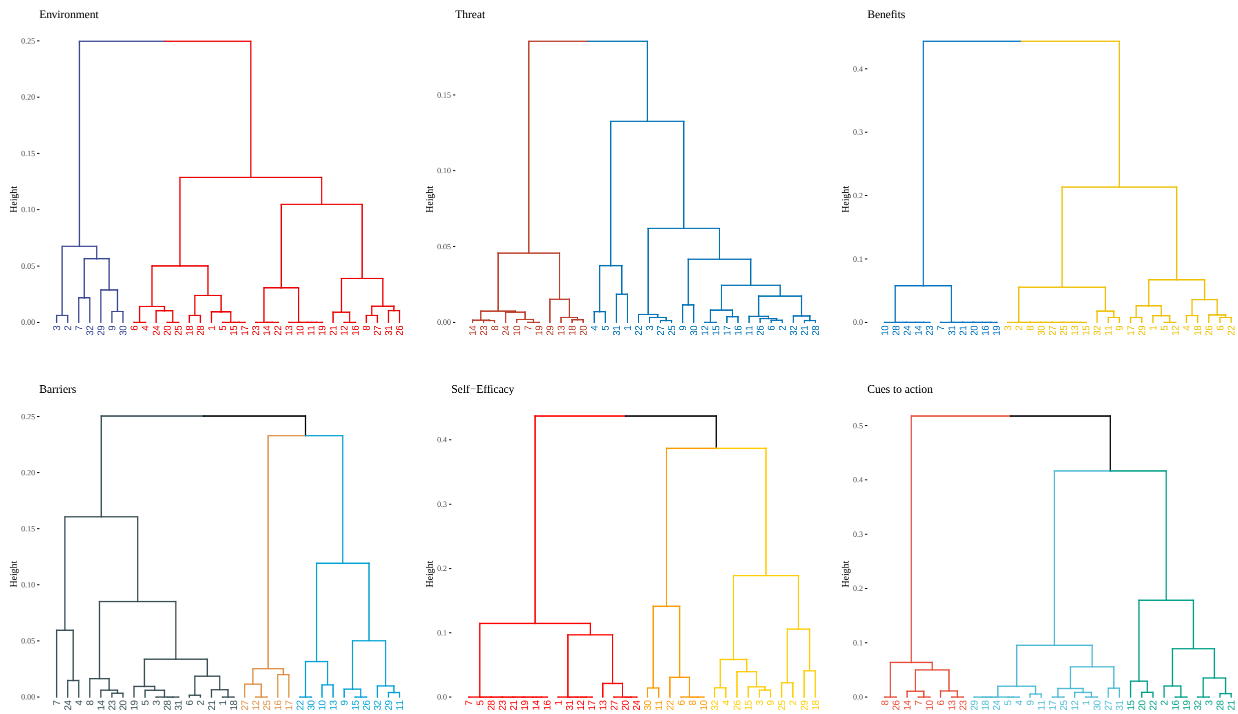
Choosing the number of classes is probably the most important aspect of classification. In fact, building a partition with too few classes risks leading to groups that are not very homogenous in their characteristics. On the other hand, building a partition with too many classes might result in groups that are not sufficiently distinct. However, here, we'd prefer to have a relatively limited number of classes, as our sample is very small. Indeed, we might end up with classes of relatively small numbers. The optimal number of classes can be determined in different ways. Here, we'll use the hierarchical tree to determine the optimal number of classes.

Each class in a hierarchical tree represents a group of similar individuals, their similarity being established according to Ward's method. The Ward's method or criterion seeks to minimize intra-class inertia and maximize inter-class inertia. In other words, the objective is to make sure that the individuals grouped in the same class are the most similar as possible while the individuals between classes are the most different as possible. Once the hierarchical tree is obtained, we need to select the number of classes. This choice can be made on the basis of the tree's general shape (Husson et al., 2010). For instance, it's generally accepted to cut the tree where the branches are long enough. However, there are other methods, such as finding the Q value that minimizes the following criterion :

$$\frac{\Delta(Q)}{\Delta(Q+1)}$$

Where $\Delta(Q)$ is equal to the between-inertia increase when we move from $Q-1$ to Q clusters. Taking this criterion into account, the `HCPC` function of the `FactoMineR` package calculates the optimal number of clusters (Husson et al., 2010). The optimal partition given by the function `fviz_dend` from the optimal estimation of `HCPC` is represented by Figure 6.2 (Appendix). After estimating the optimal partition, we realized that it was very complicated to interpret Environment, PT and PB with three classes. Since there's no point in having classes that can't be interpreted, we specified to the `HCPC` function that we wanted 2 classes for these three components. Figure 3.4 gives us our final partition with each class represented by a different color.

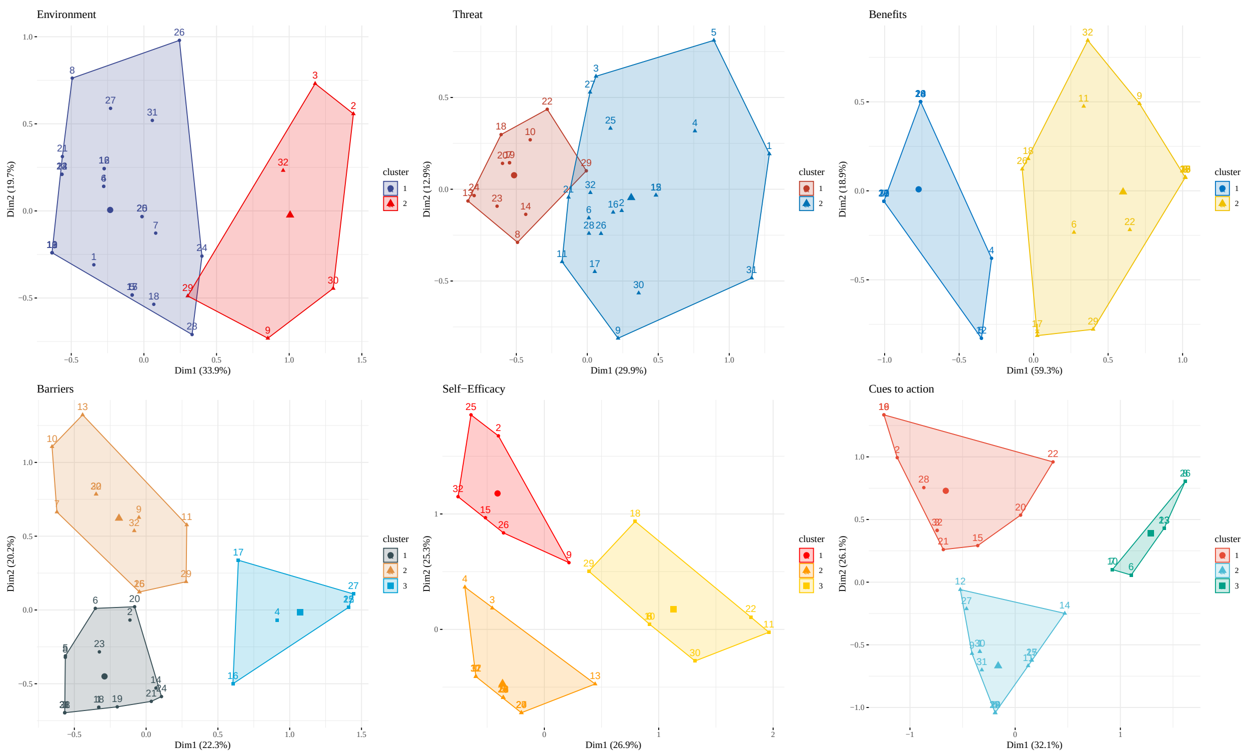
Figure 3.4: Graphical representation of hierarchical trees



Partitioning

Once we've obtained our partitions, we can move on to the next step: creating the clusters. To do this, we'll use the k-means algorithm. The k-means algorithm is a clustering approach that utilizes point-based techniques to minimize clustering error by moving cluster centers from their initial arbitrary positions (Likas et al., 2003). The k-means algorithm begins with the partition obtained in Figure 3.4 and undergoes multiple iterations before ultimately retaining the resulting partition to create clusters (Husson et al., 2010).

Figure 3.5: Graphical representation of clusters



Using the function `fviz_cluster`, we can plot our clusters as follows (Figure 3.5). We see that each component has the same number of partitions as there are clusters. Each cluster seems quite distinct from the others. So, it should be relatively simple to differentiate and identify the group of individuals belonging to each cluster.

Cluster identification

We note similarities in the composition of the first three components of Figure 3.5. Indeed, for each of the three components, each cluster splits individuals into two groups. For the environmental component, both clusters display distinct attitudes and socio-economic characteristics. Cluster 1, include a broad age range and predominantly females who demonstrates more environmentally conscious attitudes, supporting reforestation and restoration efforts. They are varied in education and income levels and are either active workers or students (Table 6.9 6.3 Appendix). Cluster 2, younger and largely male, displays less environmentally conscious views, favoring economic growth over climate action and disregarding urban HWs as significant issues. Their education and income levels are generally lower, and they primarily students (Table 6.9 6.3 Appendix).

As far as PT is concerned, Cluster 1 and Cluster 2 have distinct socio-economic and perceptual differences. Cluster 1 is mainly composed of older people with equal male and female representation (Table 6.10 Appendix). This cluster has a more varied education, relatively higher income, with the majority being homeowners and active in terms of professional category. They also show higher perceived susceptibility and severity to heat and health risks (Table 6.5 Appendix). Cluster 2 predominantly consists of young females with a high level of education and lower income (Table 6.10 Appendix). Despite their awareness of climate change and its effect on HWs, this group exhibits lower perceived susceptibility to heat-related health risks, although they still recognize severe outcomes from heat exposure (Table 6.5 Appendix).

In terms of PB, there are substantial differences between Cluster 1 and Cluster 2. Cluster 1 primarily consists of a mix of ages with more females and individuals of varied education (Table 6.11 Appendix). They have a mid-range income, and a majority are active professionally, unmarried, and homeowners. This cluster perceives a high benefit of MMs for comfort during HWs, reducing air conditioning dependence, lowering local temperature, improving neighborhood aesthetics, air quality, and fostering local pride (Table 6.5 Appendix). On the other hand, Cluster 2, largely consists of younger individuals with an equal gender representation, possessing a wide educational background but with lower income (Table 6.11 Appendix). A majority of this cluster are students, renters, and live alone. Contrary to Cluster 1, they perceive considerably lesser benefits from cooling strategies in all the listed areas, suggesting a significant variance in perception between the two groups (Table 6.5 Appendix).

For the last three components, we get 3 clusters, probably corresponding to what we observed earlier in Figure 3.3. Regarding the PBAR clusters, three distinct groups can be identified based on both socioeconomic characteristics and attitudes towards potential challenges. Cluster 1 is primarily composed of older individuals, with both males and females evenly represented. Participants in this cluster have a diverse range of education levels and earn a low-to-moderate income. Most are either working or students, and many live alone. In terms of PBAR, this group acknowledges potential obstacles, but remains generally optimistic. For instance, they show concern that neighbors might not be aware of the benefits of MMs but don't perceive technical difficulties as a significant barrier (Table 6.6 Appendix). Cluster 2 includes a mix of different age groups but is predominantly female. This cluster show a higher level of concern regarding their ability to evaluate the real impact of cooling strategies on their environment. However, they don't perceive financial constraints or potential negative judgment from their peers as significant barriers (Table 6.6 Appendix). Cluster 3 is smaller and primarily made up of young individuals. This group includes a higher percentage of highly educated individuals and those earning more than 3540. When it comes to PBAR, this cluster shows high levels of concern across all areas, with significant worries about technical difficulties, potential visual or noise nuisance, and their ability to adequately assess the impact of mitigatoin measures (Table 6.6 Appendix).

In terms of SE, Cluster 1 and Cluster 2 demonstrate notable disparities. Cluster 1 primarily includes mixed-age individuals, a balanced gender distribution, and various educational backgrounds (Table 6.13 Appendix). This cluster exhibits a high degree of SE in supporting and actively participating in MMs policies but expresses reservations about financially contributing to these initiatives (Table 6.7 Appendix). On the other hand, Cluster 2 composed of older individuals, with more females, a broader range of education levels, and generally higher incomes. This group is more confident about their ability to support, promote, and financially contribute to the implementation of MMs, indicating a high level of SE (Table 6.7 Appendix). Lastly, Cluster 3 the smaller one, is mainly composed of studentrs. While this group demonstrates a certain level of SE in supporting and participating in MMs, they remain neutral about providing financial support for these initiatives, especially if the benefits do not directly impact their own neighborhoods.

Finally for the CA, Cluster 1 has a slightly higher representation of females (Table 6.14 Appendix). The education level in this group is mixed, with a larger proportion having completed 4-5 years of higher education. This group tends to disagree with most statements about CA, with the exceptions of government financial incentives and social media campaigns, for which they have mixed responses (Table 6.8 Appendix). On the other hand, Cluster 2 is characterized with a more balanced gender representation. This group has a high level of education with most having completed 6 or more years of higher education. This cluster agrees strongly with all the statements regarding CA (Table 6.8 Appendix). They seem to be more motivated to engage in mitigation measures if they are supported by peers, incentivized by the government, endorsed by their doctor, or promoted by celebrities and on social media. Lastly, Cluster 3 is composed of older individuals who are mostly active. This cluster remains mostly neutral towards the CA statements (Table 6.8 Appendix).
The Table 3.9 summarizes the content discussed above. For each component is associated the number of the cluster corresponding to the one displayed in the Figure 3.5 and associated with the degree of perception. We have designated moderate individuals who responded predominantly neutral to the statements. We also integrated age, gender and level of education to get an overview of the population of each cluster. This table makes it easier to see the relationships that may exist between clusters and the various variables. For example, we can see that people with the highest PT level tend to be older. Similarly, we can see that individuals with the lowest benefit levels tend to be younger. A more detailed examination of these relationships will follow in the next section.

Table 3.9: Summary of Cluster Correspondences and Socio-economic Characteristics

Component	Cluster	Level	Age	Gender	Education
Environmental awareness	1	Higher	Mixed	Female	Varied
	2	Lower	Younger	Male	Lower
Perceived Threat	1	Higher	Older	Equal	Varied
	2	Lower	Younger	Female	High
Perceived Benefits	1	Higher	Mixed	Female	Varied
	2	Lower	Younger	Equal	Varied
Perceived Barriers	1	Moderate	Older	Equal	Varied
	2	Lower	Mixed	Female	Mixed
	3	Higher	Younger	Mixed	High
Self-efficacy	1	Lower	Mixed	Equal	Varied
	2	Higher	Older	Female	Varied
	3	Moderate	Younger	Mixed	Lower
Cues to action	1	Lower	Mixed	Female	Varied
	2	Higher	Mixed	Equal	High
	3	Moderate	Older	Mixed	Varied

To complete our cluster analysis, we wanted to study the links between WTP and the respective clusters. As we saw earlier, the distribution of our WTP was very sparse (Table 3.2). Thus, we chose to group the WTP into 5 different categories. Table 3.10 shows the distribution of each clusters for each and every categories of the WTP. The first and lowest category is dominated by most environmentally engaged individuals who perceive lower threats and lower barriers. SE is evenly split between high and moderate individuals, and CA are distributed evenly between high and low. The second category is the most represented one, individuals in this category shows a full engagement for environmental matters and a high degree of SE. Interestingly, despite the higher WTP, these individuals also perceive a lower threat level and equally high benefits and barriers. For the third category, between 20 and 30 Euros the group shows a lower perception of benefits. On the other hand, the upper category express higer benefits and surprisingly lower level of PT. Finally, in the highest WTP bracket, we observe the continued trend of engaged individuals with lower PT and higher SE. Surprisingly, despite the high WTP, these individuals perceive higher barriers and lower benefits. Nonetheless, higher CA and SE seem to play a significant role in this category. Overall, it seems that the assumptions we made in the previous chapter regarding the impact of components on the HBM do not hold. The next section will enable us to make sure of this.

Table 3.10: Distribution of the WTP according to clusters

	Level of WTP (in Euros)				
	[0-10[	[10-20[	[20-30[	[30-50[	[50-80[
Headcount (%)	5	12	6	6	3
Environmental Awareness					
Most engaged	**80**	**100**	**66,67**	**66,67**	**66,67**
Less engaged	20	0	33,33	33,33	33,33
Perceived threat					
Higher	40	41.67	50	16.67	33.33
Lower	**60**	**58.33**	50	**83.33**	**66.67**
Perceived benefits					
Higher	20	50	33.33	**66.67**	33.33
Lower	**80**	50	**66.67**	33.33	**66.67**
Perceived barriers					
Higher	20	8.33	16.67	33.33	33.33
Moderate	20	33.33	**66,67**	16,67	0
Lower	**60**	**50**	16,67	**50**	**66.67**
Self-Efficacy					
Higher	40	**58.33**	33.33	**83.33**	**66.67**
Moderate	40	16.67	**66.67**	0	0
Lower	20	25	0	16.67	33.33
Cues to action					
Higher	40	33.33	**66.67**	50	**66.67**
Moderate	20	**50**	0	0	0
Lower	40	16.67	33.33	50	33.33

3.3 Econometrical results

In the preceding section, the utilization of descriptive statistics facilitated the identification of associations between certain variables, however, the magnitude of these associations remained undefined. The fundamental objective of the present econometric section is to convert qualitative assertions, which states positive or negative correlation between one or multiple variables, into quantitative propositions that provide us with meaningful insights into the magnitude of the associations. In this study, our objective is to look at the impact of the HBM components and the modyfing factors on the WTP for a Miyawaki UMF.

3.3.1 Ordered logit

As we saw earlier, to express the relationship between our WTP and our variables, we'll need to use an ordered logit regression as well as a simple logisitic regression. We'll start by dealing with ordered regression. Indeed, our WTP is a quantitative variable composed of several modalities ordered in a logical order, from the lowest amount to the highest amount in euros. The first step is to check whether the different categories of our WTP have sufficient sizes. As we saw earlier (Table 3.2), some modalities don't have enough numbers. So we'll group them as follows (Table 3.11) to obtain 5 mutually exclusive categories as we did in Table 3.10.

Table 3.11: Grouping modalities for WTP

Category	Modalities (en Euros)	N (%)
1	[0-10[	15.6
2	[10-20[	37.5
3	[20-30[	18.8
4	[30-50[	18.8
5	[50-80[	9.4

Since we have no quantitative variables, we can proceed directly to the test of independence between qualitative variables. The χ^2 test of independence allows us to detect the potential presence of correlation between qualitative variables. Figure 6.3 (Appendix) shows the p-value associated with each variable. Here, we want a p-value greater than 0.05 to be able to reject the alternative hypothesis of dependence between the variables at the 5% threshold. Here, we can see that several variables are dependent on each other. Initially, we will still estimate a model with all variables to see if this poses a problem.

We can now estimate a first model using the `polr` function from the `MASS` library. This first estimate, under the assumption of error homoscedasticity, will enable us to check whether the thresholds established above for WTP are significant. In our first estimate of `polr` with all variables, the function gives us the following error message : *design appears to be rank-deficient, so dropping some coefs* (Figure 6.5). This message suggests that the matrix of explanatory variables used to fit the model is linearly dependent. This means that there is a perfect linear relationship between some of them. Because of this warning, we can't perform a `summary` on the regression (Figure 6.5). We note that adding the `Hess = TRUE` option to the `polr` function allows us to use the `summary` function, but renders the results unusable afterwards.

To double-check this finding, we estimate the same model with the `clm` function from the `ordinal` package (Christensen, 2022), which gives us two warnings : *Hessian is numerically singular: parameters are not uniquely determined* and *Absolute convergence criterion was met, but relative criterion was not met* (Figure 6.9). Additionnaly, when we perform the `summary` function, the function returns NAs. If this is potentially caused by multicollinearity, warning messages could possibly indicate that the sample is too small and responses are not balanced enough. When we check for multicolinearity using a vif test, the function gives us NA's and error messages (Figure 6.7).

To try to resolve this problem, we'll remove the most dependent variables. However, it is difficult to identify precisely which variables are correlated with each other. To solve this problem, we can use an MCA, as before. Indeed, using an MCA will enable us to see on a graph the variables that are closest to each other.In the Figure 6.8 (Appendix), there appears to be an association between homeownership and PCS. This is confirmed by the chi2 test, which has a p-value close to 0 (Figure 6.3 Appendix). After analyzing the MCA and the independence matrix, we end up with the following matrix (Figure 6.4). We obtain an independence matrix with p-values that all reject the alternative hypothesis. We can therefore estimate a model with nine variables (Figure 6.11). Once again, we are unable to estimate the models with the `polr` function because of the following message: *glm.fit: fitted probabilities numerically 0 or 1 occurredError in optim(s0, fmin, gmin, method = "BFGS", ...) : initial value in 'vmmin' is not finite* (Figure 6.10). We then re-estimate the same model with the `clm` function, which this time gives us results. In this model, only the fact of experiencing heat-related health problems is significant, at the 10% threshold. Moreover, no thresholds are significant (Figure 6.11). By calibration, we replaced two variables in this model and obtained a model with three significant variables (Figure 6.12). Unfortunately, for these models, there is still no thresholds that is significant.

In an attempt to solve this problem, we're going to estimate the last 9-variable model, but reducing the number of thresholds to three. This time, we manage to estimate a model with the `polr` function. However, the results appear rather strange (Figure 6.13). Indeed, we observe very high coefficients and extremely low standard deviations. If the function worked, there must be a problem with the variable CA, Status and healthissue. Removing these three variables, we obtain a model with two significant modalities and still no significant WTP thresholds (Figure 6.14). We therefore decide to return to the model with 5 thresholds and three significant variables to pursue our analysis. It's worth noting that even if we continue our analysis, the results will be *de facto* not robust.

To continue this analysis, we'll perform a variable selection using the step procedure. The three different step procedures - forward, backward and both - give us the same results and retain 4 variables. Table 3.12 gives us the associated coefficients for each variable and threshold in this regression. We can see that, apart from 1 threshold, all variables and thresholds are significant. Thus, the 5-class split makes sense for 4 of the categories. Moreover, with regard to the HBM components, we observe that perceiving lower profits ($p<0.1$) and higher ($p<0.1$) or lower ($p<0.05$) barriers has a significant impact on the probability of belonging to one of the 5 WTP categories. In addition, at a threshold of 1 %, being married and having had previous heat-related health problems seem to have an impact (negative for the former and positive for the latter). The value of McFadden's pseudo square R^2adj is 0.16. The model's goodness of fit can therefore be considered relatively good. Furthermore, the prediction percentage is 37.5 %, which can be considered correct since it is below 50 % (Table 3.12).

Table 3.12: Results given by the ordered regression

	Dependent variable:
	Willingness to pay
Perceived benefits	
Lower	-1.430^{*}
	(0.817)
Perceived Barriers	
Lower	2.008^{**}
	(0.996)
Higher	1.855^{*}
	(1.001)
Socioeconomic caracteristics	
Married (Yes=1)	-3.666^{***}
	(1.217)
Health issue (Yes=1)	4.285^{***}
	(1.652)
WTP threshold	
1|2	0.004^{***}
	(0.8)
2|3	0.754
	(0.641)
3|4	0.058^{*}
	(0.693)
4|5	0.001^{***}
	(0.955)
Observations	32
Log Likelihood	−40.368
R^2 *McFadden*	0.16
Forecast	37.5 %
Note:	*p<0.1; **p<0.05; ***p<0.01

Using an `anova` test to compare the model below with a model containing only the constant (we cannnot perform `lrtest` on `clm` functions), we find that the probability of accepting the nullity of all variable coefficients is null (p<0.01), showing that the estimated model is of interest. To continue and interpret our coefficients, we'll use the odd-ratio as we're dealing with categorical variables. Table 3.13 gives us the odd-ratio associated with each significant variable. Here, we could say that individuals who see the least benefit from installing a coolling strategy are $\frac{1}{0.24}$ =4.17 less likely to have a WTP greater than 10 euros than those who see more benefit from installing a cooling strategy. The same goes for 20, 40 and 50 Euros.

As far as PBAR are concerned, we can say that people who perceive few barriers to the implementation of cooling strategies are 7.45 times more likely to have a WTP greater than 10 euros than people who are more moderate about potential barriers. Once again, the same applies to the higher categories. Surprisingly, the odd-ratio is almost identical for the two extreme PBAR values. This means that regardless of one's degree of perception, the fact of not being moderate increases the probability of belonging to one of the WTP categories. Finally, we observe an extremely high odd-ratio for the health issue, indicating that people who have already had heat-related health problems are 72 times more likely to have a WTP greater than 10 euros than those who have never had health problems. This observation leaves us perplexed as to the relevance of our models and data.

Table 3.13: Odds Ratio

Variable	Coefficient
Perceived benefits	
Lower	0.24
Perceived barriers	
Lower	7.45
Higher	6.39
Socioeconomic variables	
Married (Yes=1)	0.026
Health issue (Yes=1)	72.58

We'll now check whether our model satisfies the proportional odds assumption. To do this, we'll use the `vglm` function from the `VGAM` package. A priori, the equality of slopes hypothesis seems to be respected at the 5 % threshold for the first three variables (Figure **??** Appendix). However, for the health issue variable, the function appears to fail.

Until now, we've assumed that the errors in our model were homoscedastic. We're now going to take into account the potential heteroscedasticity of our errors in our models, using the|verb|oglmx| function from the package of the same name. After an initial estimation assuming that our four variables could be sources of heteroscedasticity, we decided to remove the Health issue variable as it posed too many problems with the estimations (Figure 6.20 Appendix).
We therefore estimate a model in which we assume three variables that could be a source of heteroscedasticity. A priori, none of our three variables causes a heteroscedasticity concern (Figure 6.21 Appendix). To conclude, we'll look at the marginal effects in relation to the sample mean level, considering the binary explanatory variables as dummies (Figure 6.22 Appendix). These marginal effects show us the impact of each variable on the different WTP categories. We note that the variables have no effect on the last category of WTP, those who contributed between 50 and 80euros. We also note that being married has a significant impact on all WTP categories ($p<0.05$). Finally, at the 1% risk threshold, receiving less profit from the installation of cooling strategies decreases the probability of being in the third WTP category and increases

the probability of being in the second category. Finally, for PBARs, perceiving many and few barriers had a significant impact ($p<0.01$) on the probability of being in the second WTP category.

3.3.2 Logit

Since ordered multinomial models didn't give us very convincing results, we decided to dichotomize the variable in an attempt to apply a logit model to our study. Thus, our explanatory variable will take the value of 1 if the person has a WTP greater than 20 Euros and O otherwise (Table 3.14).

Table 3.14: Willigness to pay : Logit

Category	Modalities (in Euros)	N (%)
0	[0-20[	53.1
1	[20-80[	46.9

We have decided to estimate directly the last model we used with the ordered logits, to see if our database doesn't cause problems with the `glm` function in the `stats` package. With only three variables, the p-values all tend towards 1 (Figure 6.23 Appendix) which shows us that the same problem is also present for logit. However, the same result occurs when variables are removed. We've tried this with every possible combination of variables, and the results are always the same: p-values which all converge to 1. As we mentioned earlier, this problem probably arises from the sample size and structure of the data, making it difficult for the model to converge correctly and estimate realistic probabilities. If there had been a multicolinearity problem here, it would have been possible to run the function with only one variable, which is not the case. We'll finish by saying that when we tried out these models on Stata, the software kept looping around without giving any results.

Chapter 4

Conclusion

In the face of an increasing global warming, gaining a deeper understanding of public perceptions towards heat waves (HWs) mitigation measures has emerged as a critical needs. This study was designed to try to address the gap in the existing literature by investigating individuals' willingness to pay (WTP) for urban heat islands (UHIs) mitigation policies, specifically in the context of a French city, Nantes. Using both the health belief model (HBM) and the contingent valuation method, we focused into the influences of health beliefs about the impacts of HWs on individuals' behavioral attitudes, particularly their WTP for a Miyawaki urban micro-forest (UMF). To achieve this, we designed an online questionnaire, which allowed us to gather relevant data. Through the application of Hierarchical clustering on principal components (HCPC), we successfully identified diverse groups within each component of the HBM. If we were able to distinct individuals based on certains statements, except for Self-efficacy, our findings suggest that the majority of individuals are of well aware of HWs threats as well as potential benefits from mitigation measures. As our population is relatively young, it's not surprising that we found that the general population studied was very aware of environmental issues. With regard to the impact of HBM on WTP, our results were also less than convincing. Our research indactes that perceiving lower and higher barriers could positively influence WTP compared to individuals perceiving more moderate barriers. We were unable to observe the significant impact of PT as we might have expected. Moreover, our descriptive analysis indicated that the highest contributors were those with the lowest PT levels, which, if verified econometrically, would have been contrary to our assumptions. Regarding socio-economic variables, our results gave us poor insights. We were unable to observe any significant impact of variables such as age or gender, as can be observed in the literature. However, our results reveal that being married and perceiving fewer benefits can negatively impact the probability of contributing to the financing of MMs. If our results were robust, the impact of marital status would have been in line with the literature. Nonetheless, these results underline the multidimensional nature of the question, in which individual and socio-economic characteristics become interlinked with perceptions and attitudes towards HW risks and mitigation measures. As we've seen, our research is not without limitations. As with any study reliant on self-reported questionnaire data, factors such as response bias, sampling bias, and the scope of study should be duly considered when interpreting the findings. Our econometric results and methods were not entirely robust, implying that our results might be biased and should be treated with caution when informing public policy decisions. Future research and public policies should continue to investigate individual beliefs about HWs risks. A potential direction for subsequent studies could be to apply others psychological models like the theory of planned behavior, which might provide a better understanding of attitudes and behaviors towards HWs mitigation measures. Despite its limitations, this study provides valuable insights that could the starting point of a more in-depth and robust research in the future, crucial in our effort to combat the challenges of climate change.

Chapter 5

Discussion

We recognize several limitations and challenges that have influenced our results and their interpretation. First and foremost, the low response rate to our questionnaire was a considerable setback. Undeniably, a larger pool of responses would have contributed to a richer, more diverse dataset, and possibly more nuanced results. However, we acknowledge that the limitations of our questionnaire extended beyond just the response rate. After reflection, the design of our questionnaire may have been overly complex or ambitious. The multitude of questions may have been burdensome to respondents, affecting both the response rate and the quality of the answers we received. Due to all these biases, it is impossible for us to verify the hypotheses established by scientific literature. Future studies should consider spending more time refining the questionnaire design to ensure the questions are succinct, relevant, and engaging enough to capture individuals' perceptions effectively. Moreover, the section of the questionnaire focused on environmental awareness was arguably too ambiguous. The options provided were fairly easy to agree with, reducing the discriminative power of the responses. In retrospect, this section could have been redesigned or possibly withdraw without significant loss of valuable data. Also, our initial intention was to include quantitative variables. However, due to incomplete responses, we were unable to integrate these into our study, representing another limitation.

Chapter 6

Appendix

6.1 Chapter 3

6.1.1 Sample representativeness using the quota's method

According to INSEE, the city of Nantes has 318,808 inhabitants of which 52% are women and 48% men [1].

Table 6.1: Cross-Tabulation for quotas method

	Female	Male	Sum
Observed population	19	14	32
Theoretical population	$32 \times 0.52 = 16.64$	$32 \times 0.48 = 15.36$	92
Distribution in the total population	0,594	0,406	1

$$\chi^2_{observed} = \frac{(19-16.64)^2}{16.64} + \frac{(14-15.36^2)}{15.36} = 0.46 \text{ à} 10^{-3} \text{ près.}$$

$$\chi^2_{theoritical}(k=1) = 3.84$$

$$\chi^2_{observed} < \chi^2_{theoritical}$$

The calculated value is inferior to the theoretical value of the sample. The sample can be considered as representative regarding Nantes gender's distribution.

[1] Dossier complet, Commune de Nantes (44109)

Figure 6.1: Caption

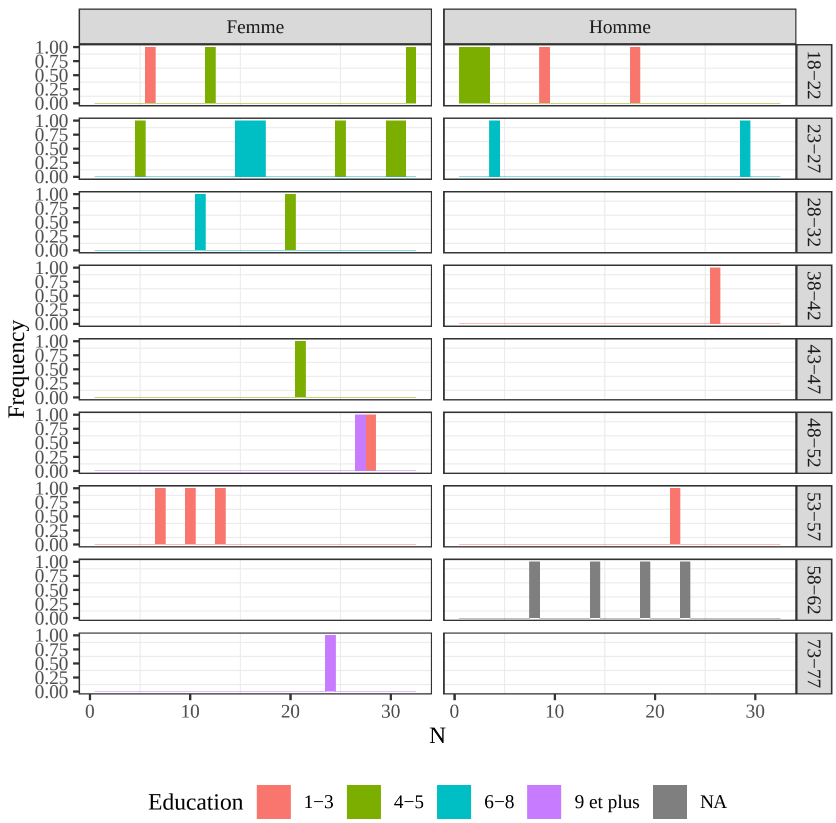


Table 6.2: Reasons for which WTP is equal to zero

ID	Name	Values	N
1	Manque de ressources financières, difficultés financières	No	6 (60.0%)
		Yes	4 (40.0%)
2	Priorité à d'autres projets personnels ou associatifs	No	8 (80.0%)
		Yes	2 (20.0%)
3	Pas convaincu(e) de l'efficacité des micro-forêts de Miyawaki	No	10 (100.0%)
4	Préférerais soutenir d'autres solutions environnementales	No	10 (100.0%)
5	Estime que le financement devrait être pris en charge par les pouvoirs publics	No	4 (40.0%)
		Yes	6 (60.0%)
6	Manque d'information sur le projet	No	8 (80.0%)
		Yes	2 (20.0%)
7	Pas d'intérêt personnel pour la question environnementale	No	10 (100.0%)
8	Ne fréquente pas suffisamment le quartier concerné	No	10 (100.0%)
9	Ne sais pas / Ne souhaite pas répondre	No	10 (100.0%)
10	Autre	No	42 (97.7%)
		Déjà trop largement taxé en tant que célibataire	1 (2.3%)

6.1.2 Modalities adjustment

Environmental awareness

We noticed that the opinion of the population studied was fairly consensual. Indeed, the population studied seems generally well aware of environmental issues. So, to make the results more perceptive, we decided to divide the population into two categories: those who answered SD and those who didn't. We assumed that those who answered SD were those with the greatest environmental awareness. In fact, we assume that those who answer SD are those with the strongest convictions and the most self-confident people. So, we dichotomize between these people and the others. So we have the Most Engaged (Most Engaged) and the Least Engaged (LE).

Perceived threat

As our sample is relatively small, and the ACM is sensitive to small nuMost benefitsers, we have chosen to systematically group SD with D and SA with A. For statements 1-2-4-8-10-12-13-14, we considered that people who answered N felt less vulnerable, as otherwise they would be more likely to answer A or SA to this type of statement. For question 3, we kept the N, as the proportion of individuals who answered N was high. Finally, we chose to delete question 7, as only 1 person answered something other than SA or A.

Perceived benefits

As with the environmental component, the sample as a whole receives benefits. To differentiate between individuals, we will further segment into those who receive the most benefits (SA) and those who do not. We end up with two categories: those who receive the most benefits (Most benefits) and those who receive the least benefits (Less benefits).

Perceived barriers

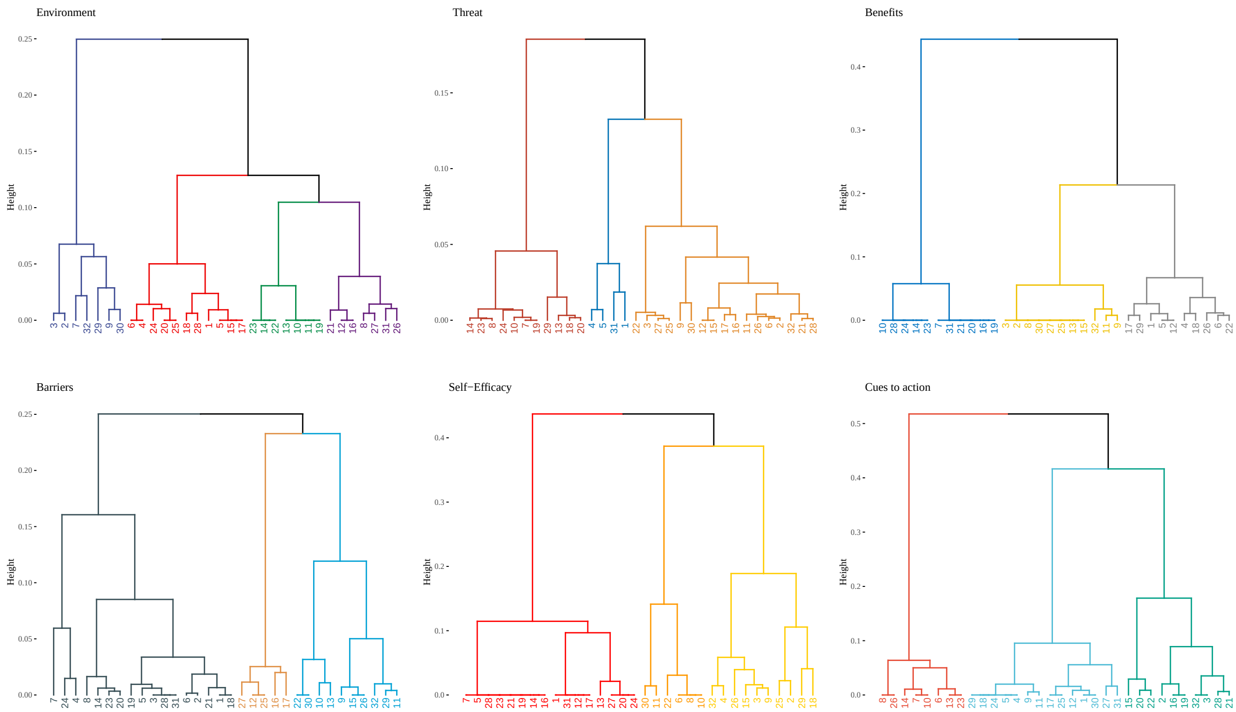
For this component, we chose to delete question 1, as only 1 person is A and 12.5% are N. For questions 2-3-4-5-6, we grouped together SA/A and SD/D and left the Ns, which represented a large nuMost benefitser of individuals.

Self-Efficacy and Cues to action

For these two components, no changes have been made.

Hierarchical Clustering on Principal Components

Figure 6.2: Hierarchical trees



Cluster composition

Table 6.3: Cluster composition : Environmental awareness

	Cluster 1	Cluster 2
N	6	26
Statement	Distribution (%)	
La hausse des températures mondiales est principalement due à des variations naturelles du climat plutôt qu'aux activités humaines		
Less Engaged	26.92	33.33[1]
Most Engaged	73.08	66.67
L'interdiction des véhicules à essence et diesel dans les centres-villes est une mesure excessive pour lutter contre la pollution de l'air.		
Less Engaged	46.15	50.00
Most Engaged	53.85	50.00
Les efforts pour lutter contre le réchauffement climatique pourraient nuire à la croissance économique et à la création d'emplois		
Less Engaged	38.46	66.67
Most Engaged	61.54	33.33
Les canicules ne sont pas un problème majeur dans les villes et ne nécessitent pas d'actions spécifiques pour les atténuer		
Less Engaged	7.69	66.67
Most Engaged	92.31	33.33
Les entreprises et les gouvernements devraient se concentrer davantage sur l'adaptation aux impacts du changement climatique plutôt que sur la réduction des émissions de gaz à effet de serre.		
Less Engaged	57.69	83.33
Most Engaged	42.31	16.67
Le développement des transports en commun et des pistes cyclables n'est pas une priorité pour l'amélioration de la qualité de vie en ville.		
Less Engaged	11.54	83.33
Most Engaged	88.46	16.67
Les actions de reforestation et de restauration des écosystèmes naturels ne sont pas essentielles pour lutter contre le réchauffement climatique et préserver la biodiversité.		
Less Engaged	0.00	100.00
Most Engaged	100.00	0.00

[1] *33,33% of individuals in cluster 2 are Less Engaged regarding Statement 1*

Table 6.4: Cluster composition : Perceived threat

	Cluster 1	CLuster 2
N	12	20
Statement	Distribution (%)	
Perceived Susceptibility		
Par rapport aux autres personnes de mon âge, je me considère comme étant plus vulnérable face à la chaleur.		
Agree	41.67	0.00
Disagree	58.33	100.00
Je considère que les conditions de mon logement me rendent plus vulnérable aux canicules (ex : absence de climatisation, mauvaise isolation, etc.).		
Agree		41.67
40.00		
Disagree	58.33	60.00
Je pense que le réseau de santé de ma région est capable de faire face aux problèmes de santé liés aux canicules.		
Agree	8.33	25.00
Disagree	66.67	45.00
N	25.00	30.00
La chaleur a un impact important sur mon choix d'activités en plein air pendant l'été.		
Agree	100.00	85.00
Disagree	0.00	15.00
L'intensité des canicules est amplifiée par le changement climatique.		
Agree	100.00	100.00
La fréquence des canicules est amplifiée par le changement climatique.		
Agree	100.00	100.00
Mon mode de vie et mes activités quotidiennes me rendent plus susceptible d'être affecté par une canicule.		
Agree	83.33	30.00
Disagree	16.67	70.00
Perceived Severity		
Une exposition prolongée au soleil pourrait augmenter les risques que je développe un cancer de la peau.		
Agree	100.00	90.00
Disagree	0.00	10.00
Une exposition prolongée à de fortes chaleurs risque d'altérer grandement mes capacités physiques/intellectuelles au point de ne plus pouvoir travailler.		
Agree	100.00	40.00
Disagree	0.00	60.00
Si je suis déshydraté(e) pendant une période prolongée, je risque d'avoir des maux de tête et des vomissements.		
Agree	100.00	90.00
Disagree	0.00	10.00
Si je suis exposé(e) à des températures élevées pendant une période prolongée, je risque de perdre connaissance.		
Agree	91.67	75.00
Disagree	8.33	25.00
Je pourrais éviter de sortir dans les rues de la ville pendant une vague de chaleur pour éviter les risques pour ma santé.		
Agree	100.00	50.00
Disagree	0.00	50.00
Si je ressens des symptômes tels que des crampes musculaires ou des étourdissements pendant une vague de chaleur, j'irais consulter un médecin immédiatement.		
Agree	75.00	0.00
Disagree	25.00	100.00
Les canicules peuvent me causer des problèmes de santé mentale, comme l'anxiété ou la dépression, en raison du stress lié à la chaleur.		
Agree	75.00	25.00
Disagree	25.00	75.00
Je pense que les effets des canicules sur ma santé peuvent être irréversibles.		
Agree	91.67[1]	15.00
Disagree	8.33	85.00

[1] *91.67% of cluster 1 is agree with the Satement 8 of Perceived Severity*

Table 6.5: Cluster composition : Perceived benefits

	Cluster 1	Cluster 2
N	14	18
Statement	Distribution (%)	
Les îlots de fraîcheur sont essentiels pour améliorer mon confort pendant les périodes de canicule.		
Less benefits	21.43	88.89
Most benefits	78.57	11.11
Les îlots de fraîcheur pourraient réduire ma dépendance à la climatisation pendant les canicules.		
Less benefits	14.29	77.78
Most benefits	85.71[1]	22.22
Les îlots de fraîcheur ont un impact significatif sur la réduction de la température aMost bene-fitsiante dans mon quartier.		
Less benefits	7.14	94.44
Most benefits	92.86	5.56
Les îlots de fraîcheur pourraient contribuer à améliorer l'esthétique de mon quartier et rendre les espaces publics plus accueillants et agréables.		
Less benefits	0.00	61.11
Most benefits	100.00	38.89
Les îlots de fraîcheur pourraient améliorer la qualité de l'air dans mon quartier, ce qui serait bénéfique pour ma santé.		
Less benefits	0.00	72.22
Most benefits	100.00	27.78
Le fait de soutenir un projet local et durable pourrait me donner un sentiment de fierté.		
Less benefits	35.71	83.33
Most benefits	64.29	16.67

[1] *85.71% of cluster 1 perceive Most benefits to statement 2*

Table 6.6: Cluster composition : Perceived barriers

	Cluster 1	CLuster 2	Cluster 3
N			
Statement	Distribution (%)		
Je ne dispose pas des moyens financiers nécessaires pour soutenir un tel projet.			
Agree	40.00	36.36	0.00
Disagree	26.67	18.18	100.00
Neutral	33.33	45.45	0.00
Mon entourage pourrait me juger négativement si je ne soutiens pas un projet d'îlots de fraîcheur.			
Agree	6.67	9.09	16.67
Disagree	66.67	54.55	50.00
Neutral	26.67	36.36	33.33
Il pourrait y avoir des difficultés techniques liées à la mise en place et à l'entretien des îlots de fraîcheur.			
Agree	0.00	0.00	66.67
Disagree	86.67	18.18	16.67
Neutral	13.33	81.82	16.67
Les habitants du quartier pourraient ne pas être informés ou conscients de l'existence et des avantages potentiels des îlots de fraîcheur.			
Agree	60.00	54.55	83.33
Disagree	40.00	18.18	16.67
Neutral	0.00	27.27[1]	0.00
Les habitants du quartier pourraient être préoccupés par les possibles nuisances sonores ou visuelles liées à la mise en place des îlots de fraîcheur.			
Agree	0.00	0.00	83.33
Disagree	100.00	18.18	16.67
Neutral	0.00	81.82	0.00
Je ne me sens pas assez informé(e) ou compétent pour évaluer l'impact réel des îlots de fraîcheur sur mon environnement.			
Agree	13.33	81.82	83.33
Disagree	86.67	18.18	16.67
Je pense qu'il serait plus judicieux d'investir dans des solutions de climatisation intérieure8 plutôt que dans des îlots de fraîcheur.			
Disagree	100.00	100.00	100.00

[1] *27.27% of cluster 2 is neutral regarding statement 5*

Table 6.7: Cluster composition : Self-Efficacy

	Cluster 1	Cluster 2	Cluster 3
N	6	18	8
Statement	Distribution (%)		
Je me sens capable de m'impliquer activement dans des projets collectifs pour soutenir la création et l'entretien d'îlots de fraîcheur dans mon quartier.			
Agree	50.00	50.00	62.50
Disagree	33.33	27.78	12.50
Neutral	16.67	22.22	25.00
Je me sens capable de convaincre mon entourage de soutenir le projet d'îlots de fraîcheur.			
Agree	66.67	100.00	37.50
Disagree	33.33	0.00	25.00
Neutral	0.00	0.00	37.50
Je me sens capable de contribuer financièrement à la mise en place d'îlots de fraîcheur dans mon quartier.			
Agree	0.00	94.44	25.00
Disagree	100.00	0.00	0.00
Neutral	0.00	5.56	75.00
Je suis prêt à soutenir financièrement la création d'îlots de fraîcheur dans d'autres quartiers, même si cela ne profite pas directement à mon propre quartier.			
Agree	0.00	88.89	0.00
Disagree	83.33	11.11	0.00
Neutral	16.67	0.00	100.00[1]

[1] *All individuals in cluster 3 are neutral regarding statement 4*

Table 6.8: Cluster composition : Cues to action

	Cluster 1	Cluster 2	Cluster 3
CA	10	15	7
Statement	Distribution (%)		
Je serais davantage motivé(e) à m'engager dans un projet d'îlot de fraîcheur dans mon quartier si je savais que des personnes de mon entourage y participaient aussi.			
Agree	40.00	86.67	28.57
Disagree	60.00	13.33	0.00
Neutral	0.00	0.00	71.43
Des incitations financières gouvernementales pour soutenir les projets durables augmenteraient ma motivation à investir dans ces projets.			
Agree	40.00	100.00	71.43
Disagree	30.00	0.00	0.00
Neutral	30.00	0.00	28.57
Si mon médecin me parlait de cette initiative, je serais plus enclin(e) à y participer.			
Agree	0.00	80.00[1]	14.29
Disagree	80.00	6.67	0.00
Neutral	20.00	13.33	85.71
Si des célébrités ou des personnalités publiques soutenaient et promouvaient les îlots de fraîcheur, je serais plus intéressé(e) à m'engager dans de tels projets.			
Agree	0.00	53.33	0.00
Disagree	90.00	26.67	0.00
Neutral	10.00	20.00	100.00
Si je voyais des campagnes de sensibilisation sur les réseaux sociaux, je serais plus susceptible de m'impliquer dans la création d'îlots de fraîcheur.			
Agree	30.00	93.33	0.00
Disagree	70.00	6.67	0.00
Neutral	0.00	0.00	100.00

[1] *80% of cluster 2 is agree with statement 3*

6.1.3 Socioeconomic caracterstics of each clusters

Table 6.9: Socioeconomics characteristics of clusters: Environmental awareness

Variable	Cluster 1	Cluster 2
Age	N (%)	
18-22	12.5	12.5
23-32	28.1	6.3
38-57	25.0	0.0
58-77	15.6	0.0
Gender		
Female	53.1	6.3
Male	28.1	12.5
Education		
0	12.5	0.0
1-3	25.0	3.1
4-5	21.9	12.5
6 and more	21.9	3.1
Income		
More than 3540	9.4	3.1
Between 1150 and 2150	28.1	3.1
Between 2150 and 3540	21.9	0.0
Less than 1150	21.9	12.5
PCS		
Active	37.5	0.0
Students	31.3	18.8
Inactive	12.5	0.0
Married		
No	65.6	18.8
Yes	15.6	0.0
House		
No	50.0	15.6
Yes	31.3	3.1
Owner		
No	43.8	18.8
Yes	37.5	0.0
Alone		
No	53.1	6.3
Yes	28.1	12.5

Table 6.10: Socioeconomics characteristics of clusters: PT

Variable	Cluster 1	Cluster 2
Age	N (%)	
18-22	3.1	21.9
23-32	6.3	28.1
38-57	12.5	12.5
58-77	15.6	0.0
Gender		
Female	15.6	43.8
Male	21.9	18.8
Education		
0	12.5	0.0
1-3	15.6	12.5
4-5	3.1	31.3
6 and more	6.3	18.8
Income		
More than 3540	6.3	6.3
Between 1150 and 2150	12.5	18.8
Between 2150 and 3540	15.6	6.3
Less than 1150	3.1	31.3
PCS		
Active	25.0	12.5
Students	6.3	43.8
Inactive	6.3	6.3
Married		
No	25.0	59.4
Yes	12.5	3.1
House		
No	18.8	46.9
Yes	18.8	15.6
Owner		
No	9.4	53.1
Yes	28.1	9.4
Alone		
No	18.8	40.6
Yes	18.8	21.9

Table 6.11: Socioeconomics characteristics of clusters: PB

Variable	Cluster 1	Cluster 2
Age	N (%)	
18-22	3.1	21.9
23-32	15.6	18.8
38-57	12.5	12.5
58-77	12.5	3.1
Gender		
Female	31.3	28.1
Male	12.5	28.1
Education		
0	9.4	3.1
1-3	9.4	18.8
4-5	15.6	18.8
6 and more	9.4	15.6
Income		
More than 3540	0.0	12.5
Between 1150 and 2150	25.0	6.3
Between 2150 and 3540	9.4	12.5
Less than 1150	9.4	25.0
PCS		
Active	25.0	12.5
Students	12.5	37.5
Inactive	6.3	6.3
Married		
No	37.5	46.9
Yes	6.3	9.4
House		
No	28.1	37.5
Yes	15.6	18.8
Owner		
No	18.8	43.8
Yes	25.0	12.5
Alone		
No	25.0	34.4
Yes	18.8	21.9

Table 6.12: Socioeconomics characteristics of clusters: PBAR

Variable	Cluster 1	Cluster 2	Cluster 3
Age		N (%)	
18-22	15.6	6.3	3.1
23-32	9.4	12.5	12.5
38-57	6.3	15.6	3.1
58-77	15.6	0.0	0.0
Gender			
Female	21.9	21.9	15.6
Male	25.0	12.5	3.1
Education			
0	12.5	0.0	0.0
1-3	9.4	18.8	0.0
4-5	21.9	6.3	6.3
6 and more	3.1	9.4	12.5
Income			
More than 3540	0.0	6.3	6.3
Between 1150 and 2150	21.9	6.3	3.1
Between 2150 and 3540	6.3	15.6	0.0
Less than 1150	18.8	6.3	9.4
PCS			
Active	15.6	15.6	6.3
Students	21.9	15.6	12.5
Inactive	9.4	3.1	0.0
Married			
No	43.8	25.0	15.6
Yes	3.1	9.4	3.1
House			
No	34.4	21.9	9.4
Yes	12.5	12.5	9.4
Owner			
No	25.0	21.9	15.6
Yes	21.9	12.5	3.1
Alone			
No	18.8	25.0	15.6
Yes	28.1	9.4	3.1

Table 6.13: Socioeconomics characteristics of clusters: SE

Variable	Cluster 1	Cluster 2	Cluster 3
Age		N (%)	
18-22	9.4	9.4	6.3
23-32	6.3	18.8	9.4
38-57	3.1	15.6	6.3
58-77	0.0	12.5	3.1
Gender			
Female	9.4	37.5	12.5
Male	9.4	18.8	12.5
Education			
0	0.0	9.4	3.1
1-3	6.3	9.4	12.5
4-5	9.4	21.9	3.1
6 and more	3.1	15.6	6.3
Income			
More than 3540	0.0	6.3	6.3
Between 1150 and 2150	3.1	25.0	3.1
Between 2150 and 3540	3.1	9.4	9.4
Less than 1150	12.5	15.6	6.3
PCS			
Active	0.0	28.1	9.4
Students	15.6	21.9	12.5
Inactive	3.1	6.3	3.1
Married			
No	18.8	46.9	18.8
Yes	0.0	9.4	6.3
House			
No	12.5	37.5	15.6
Yes	6.3	18.8	9.4
Owner			
No	18.8	28.1	15.6
Yes	0.0	28.1	9.4
Alone			
No	12.5	31.3	15.6
Yes	6.3	25.0	9.4

Table 6.14: Socioeconomics characteristics of clusters: CA

Variable	Cluster 1	Cluster 2	Cluster 3
Age	N (%)		
18-22	9.4	12.5	3.1
23-32	9.4	25.0	0.0
38-57	9.4	3.1	12.5
58-77	3.1	6.3	6.3
Gender			
Female	18.8	28.1	12.5
Male	12.5	18.8	9.4
Education			
0	3.1	3.1	6.3
1-3	6.3	6.3	15.6
4-5	15.6	18.8	0.0
6 and more	6.3	18.8	0.0
Income			
More than 3540	3.1	9.4	0.0
Between 1150 and 2150	15.6	9.4	6.3
Between 2150 and 3540	3.1	6.3	12.5
Less than 1150	9.4	21.9	3.1
PCS			
Active	15.6	9.4	12.5
Students	12.5	34.4	3.1
Inactive	3.1	3.1	6.3
Married			
No	31.3	43.8	9.4
Yes	0.0	3.1	12.5
House			
No	18.8	37.5	9.4
Yes	12.5	9.4	12.5
Owner			
No	18.8	37.5	6.3
Yes	12.5	9.4	15.6
Alone			
No	15.6	28.1	15.6
Yes	15.6	18.8	6.3

Table 6.15: Distribution of the WTP according to clusters : Row profile

	Level of WTP (in Euros)				
	[0-10[	[10-20[	[20-30[	[30-50[	[50-80[
Headcount (%)	15.6	**37.5**	18.8	18.8	9.4
Environmental Awareness					
Most engaged	12.5	**37.5**	12.5	12.5	6.25
Less engaged	3.125	0	6.25	6.25	**3.125**
Perceived threat					
Higher	6.25	**15.625**	9.375	3.125	3.125
Lower	9.375	**21.875**	9.375	15.625	6.25
Perceived benefits					
Higher	3.125	**18.75**	6.25	12.5	3.125
Lower	12.5	**18.75**	12.5	6.25	6.25
Perceived barriers					
Higher	3.125	3.125	3.125	**6.25**	3.125
Neutral	3.125	**15.625**	12.5	3.125	0
Lower	9.375	**18.75**	3.125	9.375	6.25
Self-Efficacy					
Higher	6.25	**21.875**	6.25	15.625	6.25
Neutral	6.25	6.25	**12.5**	0	0
Lower	3.125	**9.375**	0	3.125	3.125
Cues to action					
Higher	6.25	12.5	12.5	**9.375**	6.25
Neutral	3.125	**18.75**	0	0	0
Lower	6.25	6.25	6.25	**9.375**	3.125

6.2 Chapter 4

6.2.1 Ordered Logit

H_0 : The two variables X and Y are independent

H_1 : The two variables X and Y are dependant

Figure 6.3: Pearson χ^2 test of independance

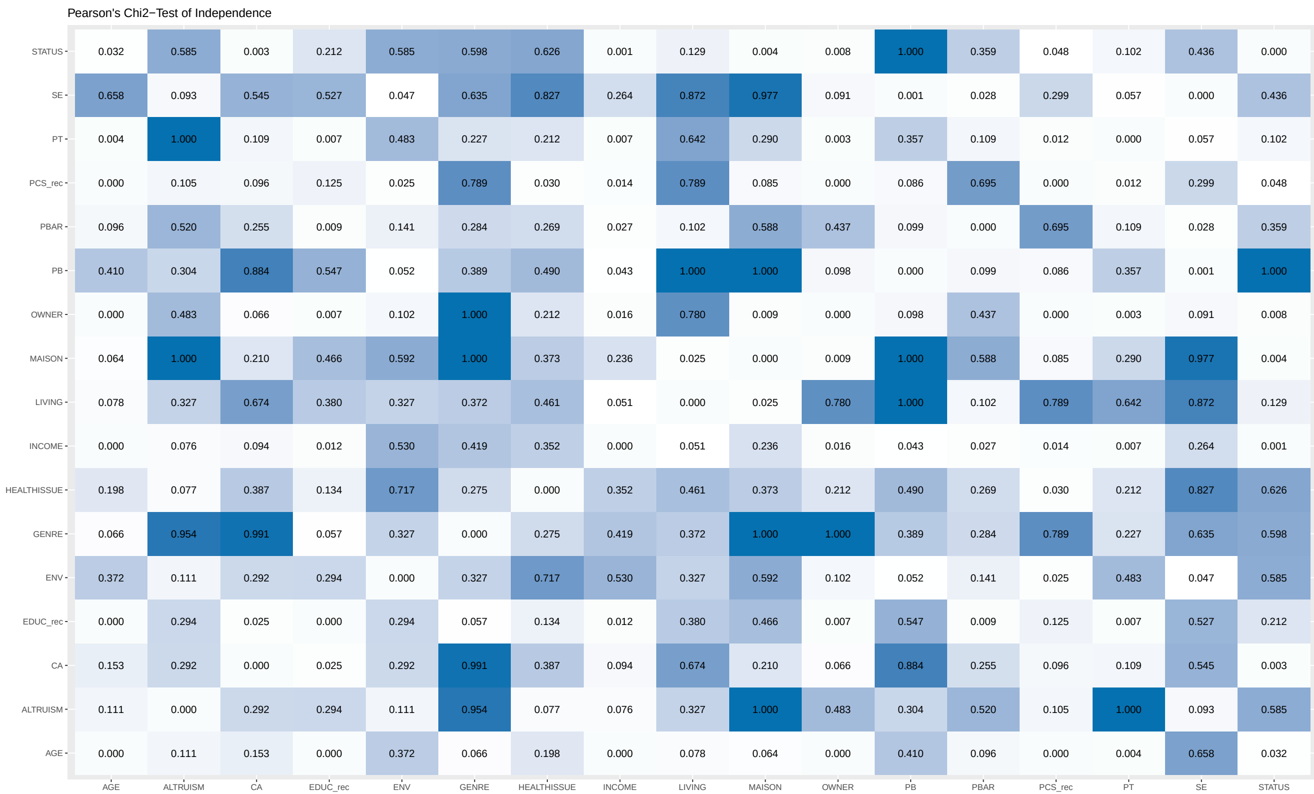


Figure 6.4: Pearson χ^2 test of independance

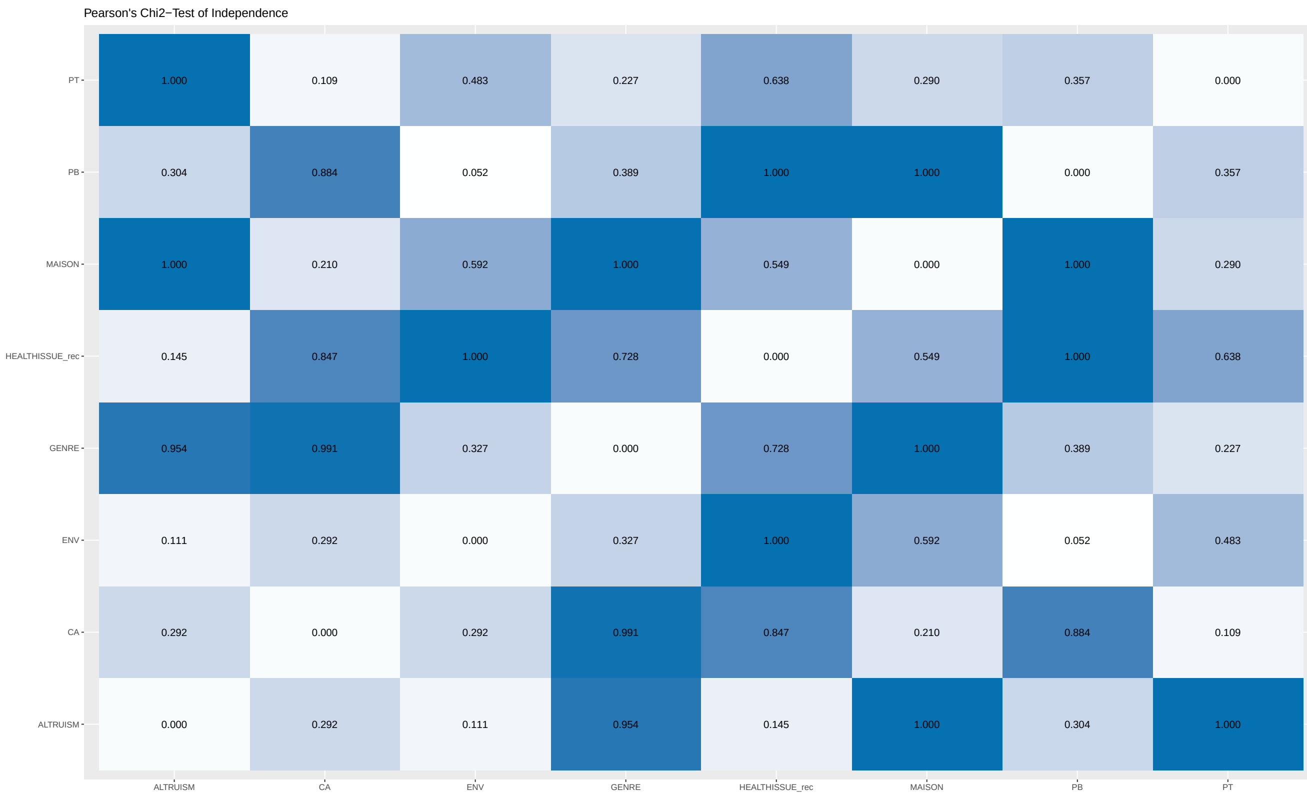


Figure 6.5: Estimation with all variables and polr Error message

```
> model_polr <- polr(WTP ~ ENV+PT+PB+PBAR+SE+CA+AGE_rec+GENRE+EDUC_rec+INCOME+PCS_rec+STATUS+MAISON+
OWNER+LIVING+ALTRUISM+HEALTHISSUE_rec, data=base, method=c("logistic"))
Warning: design appears to be rank-deficient, so dropping some coefs
> summary(model_polr)

Re-fitting to get Hessian

Error in polr(formula = WTP ~ ENV + PT + PB + PBAR + SE + CA + AGE_rec +  :
  'start' is not of the correct length
```

Figure 6.6: Testing for multicolinearity using a VIF : Full model

```
> vif(model_clm_full)
Warning: No intercept: vifs may not be sensible.Warning: diag(.) had 0 or NA entries; non-finite result
is doubtful            GVIF Df GVIF^(1/(2*Df))
ENV            NA  0              NA
PT             NA  0              NA
PB             NA  0              NA
PBAR           NA  0              NA
SE             NA  0              NA
CA             NA  0              NA
AGE            NA  0              NA
GENRE          NA  0              NA
EDUC           NA  0              NA
INCOME         NA  0              NA
PCS            NA  0              NA
STATUS         NA  0              NA
MAISON         NA  0              NA
OWNER          NA  0              NA
LIVING         NA  0              NA
ALTRUISM       NA  0              NA
HEALTHISSUE    NA  0              NA
```

Figure 6.7: Testing for multicolinearity using a VIF : Independant model

```
> vif(model_clm_full)
Warning: No intercept: vifs may not be sensible.Warning: diag(.) had 0 or NA entries; non-finite result
is doubtful            GVIF Df GVIF^(1/(2*Df))
ENV            NA  0              NA
PT             NA  0              NA
PB             NA  0              NA
PBAR           NA  0              NA
SE             NA  0              NA
CA             NA  0              NA
AGE            NA  0              NA
GENRE          NA  0              NA
EDUC           NA  0              NA
INCOME         NA  0              NA
PCS            NA  0              NA
STATUS         NA  0              NA
MAISON         NA  0              NA
OWNER          NA  0              NA
LIVING         NA  0              NA
ALTRUISM       NA  0              NA
HEALTHISSUE    NA  0              NA
```

Figure 6.8: MCA with explanatory variables

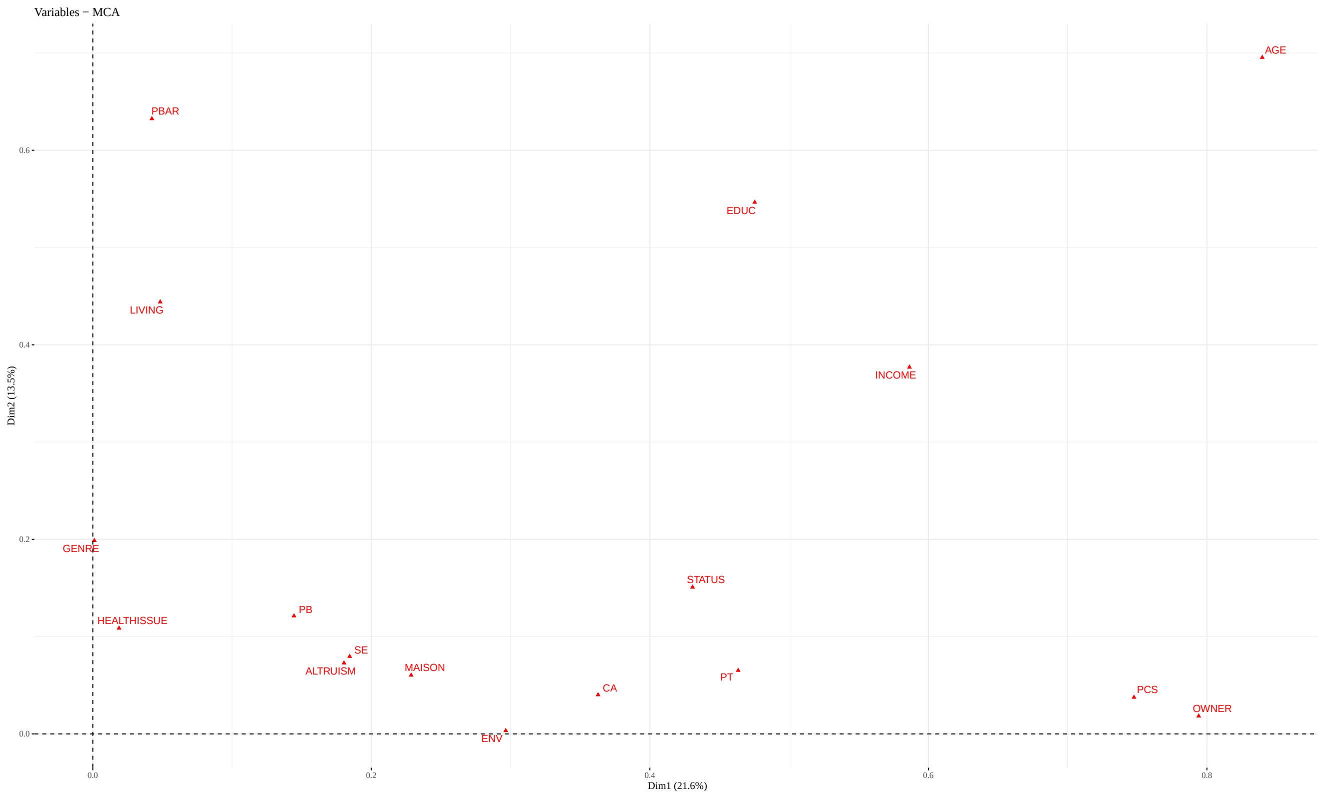


Figure 6.9: Estimation with all variables and clm : Error message

```
> model_clm_full <- clm(WTP_5 ~ ENV+PT+PB+PBAR+SE+CA+AGE+GENRE+EDUC+INCOME+PCS+STATUS+MAISON+OWNER+LIVING+ALTRUISM+HEALTHISSUE, data=b
ase)
Warning: (1) Hessian is numerically singular: parameters are not uniquely determined
In addition: Absolute convergence criterion was met, but relative criterion was not met
> summary(model_clm_full)
formula:
WTP_5 ~ ENV + PT + PB + PBAR + SE + CA + AGE + GENRE + EDUC + INCOME + PCS + STATUS + MAISON + OWNER + LIVING + ALTRUISM + HEALTHISSUE
data:    base


Coefficients:
                         Estimate Std. Error z value Pr(>|z|)
ENV2                       373.59         NA      NA       NA
PT2                        201.72         NA      NA       NA
PB2                       -161.78         NA      NA       NA
PBAR2                     -118.70         NA      NA       NA
PBAR3                      129.64         NA      NA       NA
SE2                        292.55         NA      NA       NA
SE3                        129.83         NA      NA       NA
CA2                       -110.70         NA      NA       NA
CA3                       -200.53         NA      NA       NA
AGE23-32                   349.59         NA      NA       NA
AGE38-57                   755.07         NA      NA       NA
AGE58-77                  1043.18         NA      NA       NA
GENREHomme                  14.67         NA      NA       NA
EDUC1-3                    355.11         NA      NA       NA
EDUC4-5                    -69.69         NA      NA       NA
EDUC6 et plus             -218.94         NA      NA       NA
INCOMEEntre 1150 et 2150  -448.15         NA      NA       NA
INCOMEEntre 2150 et 3540   163.92         NA      NA       NA
INCOMEMoins de 1150       -223.89         NA      NA       NA
PCSÉtudiants               -22.11         NA      NA       NA
PCSInactifs               -347.63         NA      NA       NA
STATUSOui                 -315.52         NA      NA       NA
MAISONOui                   39.22         NA      NA       NA
OWNEROui                  -775.95         NA      NA       NA
LIVINGOui                  111.78         NA      NA       NA
ALTRUISMOui                 98.57         NA      NA       NA
HEALTHISSUEOui             404.94         NA      NA       NA

Threshold coefficients:
    Estimate Std. Error z value
1|2    112.1         NA      NA
2|3    313.0         NA      NA
3|4    356.5         NA      NA
4|5    537.5         NA      NA
```

Figure 6.10: Estimation with the 9 independant variables polr : Error message

```
> model_polr <- polr(WTP_5 ~ENV + PT+ PB + SE+ CA +GENRE+MAISON+ALTRUISM+HEALTHISSUE, data=base)
Warning: glm.fit: fitted probabilities numerically 0 or 1 occurredError in optim(s0, fmin, gmin, method = "BFGS", ...) :
  initial value in 'vmmin' is not finite
```

Figure 6.11: Regression with independant variables and the polr function

```
> model_clm_9 <- clm(WTP_5 ~ ENV + PT+ PB + SE+ CA +GENRE+MAISON+ALTRUISM+HEALTHISSUE, data=base)
> summary(model_clm_9)
formula: WTP_5 ~ ENV + PT + PB + SE + CA + GENRE + MAISON + ALTRUISM + HEALTHISSUE
data:    base


Coefficients:
               Estimate Std. Error z value Pr(>|z|)
ENV2            1.53189    1.04954   1.460   0.1444
PT2             0.28469    0.89734   0.317   0.7510
PB2            -0.73384    1.04297  -0.704   0.4817
SE2             0.54378    1.16782   0.466   0.6415
SE3            -0.19233    1.18066  -0.163   0.8706
CA2             0.02494    0.80010   0.031   0.9751
CA3            -1.25762    1.05901  -1.188   0.2350
GENREHomme      0.23145    0.77710   0.298   0.7658
MAISONOui      -0.42474    0.78297  -0.542   0.5875
ALTRUISMOui     0.78926    1.16240   0.679   0.4971
HEALTHISSUEOui  3.15726    1.77553   1.778   0.0754 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Threshold coefficients:
    Estimate Std. Error z value
1|2  -1.3443     1.8931  -0.710
2|3   0.8685     1.9040   0.456
3|4   1.9932     1.9320   1.032
4|5   3.7826     2.0241   1.869
> coef(summary(model_clm))
                  Estimate Std. Error    z value   Pr(>|z|)
1|2            -1.83067396  1.5447990 -1.1850564 0.23599514
2|3             0.81176357  1.4978417  0.5419555 0.58784916
3|4             2.07359916  1.5448249  1.3422875 0.17950279
4|5             3.91894764  1.6641093  2.3549821 0.01852360
ENV2            1.70931018  1.2138389  1.4081854 0.15907618
PT2            -0.54745860  1.0144770 -0.5396462 0.58944107
PB2            -1.37690906  0.9916611 -1.3884875 0.16498865
PBAR2           1.38098766  1.0826636  1.2755464 0.20211590
PBAR3           2.27332692  1.1923882  1.9065326 0.05658114
CA2            -0.08638259  0.8204306 -0.1052893 0.91614623
CA3            -0.27697178  1.2012378 -0.2305720 0.81764735
GENREHomme     -0.09274797  0.8596991 -0.1078842 0.91408754
STATUSOui      -3.55301229  1.5767952 -2.2533125 0.02423945
ALTRUISMOui     1.05729894  1.3841563  0.7638581 0.44495183
HEALTHISSUEOui  4.36620624  1.8745033  2.3292603 0.01984528
```

Figure 6.12: Regression with significant variables and the polr function

```
> model_clm <- clm(WTP_5 ~ ENV+PT+PB+PBAR+CA+GENRE+STATUS+ALTRUISM+HEALTHISSUE, data=base)
> summary(model_clm)
formula: WTP_5 ~ ENV + PT + PB + PBAR + CA + GENRE + STATUS + ALTRUISM + HEALTHISSUE
data:    base


Coefficients:
               Estimate Std. Error z value Pr(>|z|)
ENV2            1.70931    1.21384   1.408   0.1591
PT2            -0.54746    1.01448  -0.540   0.5894
PB2            -1.37691    0.99166  -1.388   0.1650
PBAR2           1.38099    1.08266   1.276   0.2021
PBAR3           2.27333    1.19239   1.907   0.0566 .
CA2            -0.08638    0.82043  -0.105   0.9161
CA3            -0.27697    1.20124  -0.231   0.8176
GENREHomme     -0.09275    0.85970  -0.108   0.9141
STATUSOui      -3.55301    1.57680  -2.253   0.0242 *
ALTRUISMOui     1.05730    1.38416   0.764   0.4450
HEALTHISSUEOui  4.36621    1.87450   2.329   0.0198 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Threshold coefficients:
    Estimate Std. Error z value
1|2  -1.8307     1.5448  -1.185
2|3   0.8118     1.4978   0.542
3|4   2.0736     1.5448   1.342
4|5   3.9189     1.6641   2.355
> coef(summary(model_clm))
                  Estimate Std. Error    z value   Pr(>|z|)
1|2            -1.83067396  1.5447990 -1.1850564 0.23599514
2|3             0.81176357  1.4978417  0.5419555 0.58784916
3|4             2.07359916  1.5448249  1.3422875 0.17950279
4|5             3.91894764  1.6641093  2.3549821 0.01852360
ENV2            1.70931018  1.2138389  1.4081854 0.15907618
PT2            -0.54745860  1.0144770 -0.5396462 0.58944107
PB2            -1.37690906  0.9916611 -1.3884875 0.16498865
PBAR2           1.38098766  1.0826636  1.2755464 0.20211590
PBAR3           2.27332692  1.1923882  1.9065326 0.05658114
CA2            -0.08638259  0.8204306 -0.1052893 0.91614623
CA3            -0.27697178  1.2012378 -0.2305720 0.81764735
GENREHomme     -0.09274797  0.8596991 -0.1078842 0.91408754
STATUSOui      -3.55301229  1.5767952 -2.2533125 0.02423945
ALTRUISMOui     1.05729894  1.3841563  0.7638581 0.44495183
HEALTHISSUEOui  4.36620624  1.8745033  2.3292603 0.01984528
```

Figure 6.13: Regression with 3 threshold of WTP and the polr function

```
> model_polr <- polr(WTP_3 ~ ENV+PT+PB+PBAR+CA+GENRE+STATUS+ALTRUISM+HEALTHISSUE, data=base, method = c("logisti
c"))
Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
> summary(model_polr)

Re-fitting to get Hessian

Call:
polr(formula = WTP_3 ~ ENV + PT + PB + PBAR + CA + GENRE + STATUS +
    ALTRUISM + HEALTHISSUE, data = base, method = c("logistic"))

Coefficients:
                  Value            Std. Error                 t value
ENV2             3.6117 1.87699948980030995038                 1.9242
PT2             -0.2210 1.40005457590449466920                -0.1579
PB2              0.2133 1.72562867832402311308                 0.1236
PBAR2           -0.4031 1.89573326805783648474                -0.2126
PBAR3            4.9945 1.92647883333679281748                 2.5925
CA2             -1.6170 1.21567616898678765303                -1.3301
CA3            -47.7908 0.00000000000000146168   -32695894135736532.0000
GENREHomme       1.6147 1.33310394915002139449                 1.2113
STATUSOui      -88.5386 0.00000000000000007913 -1118890340010134656.0000
ALTRUISMOui      5.1331 2.38113268101432096202                 2.1557
HEALTHISSUEOui  94.6256 0.00000000000000004884  1937305769113789184.0000

Intercepts:
    Value                   Std. Error                t value
1|2                  4.8485                   2.4760                  1.9582
2|3                  8.1257                   3.0624                  2.6534

Residual Deviance: 30.04745
AIC: 56.04745
> (ctable<-coef(summary(model_polr)))

Re-fitting to get Hessian

                    Value                Std. Error                     t value
ENV2             3.6116674 1.87699948980030995038248                   1.9241707
PT2             -0.2210074 1.40005457590449466920290                  -0.1578563
PB2              0.2133231 1.72562867832402311307760                   0.1236205
PBAR2           -0.4030625 1.89573326805783648474346                  -0.2126156
PBAR3            4.9944712 1.92647883333679281747663                   2.5925388
CA2             -1.6169522 1.21567616898678765302577                  -1.3300846
CA3            -47.7908405 0.00000000000000146167712   -32695894135736532.0000000
GENREHomme       1.6147270 1.33310394915002139448745                   1.2112536
STATUSOui      -88.5386473 0.00000000000000007913076 -1118890340010134656.0000000
ALTRUISMOui      5.1330843 2.38113268101432096202075                   2.1557322
HEALTHISSUEOui  94.6255693 0.00000000000000004884390  1937305769113789184.0000000
1|2              4.8484650 2.47604347822508996657120                   1.9581502
2|3              8.1257132 3.06235992037748072647219                   2.6534155
> p <- pnorm(abs(ctable[,"t value"]),lower.tail=FALSE)*2
> p2<-round(p,4)
> (ctable<-cbind(ctable,pvalue=p2))
                    Value                Std. Error                     t value pvalue
ENV2             3.6116674 1.87699948980030995038248                   1.9241707 0.0543
PT2             -0.2210074 1.40005457590449466920290                  -0.1578563 0.8746
PB2              0.2133231 1.72562867832402311307760                   0.1236205 0.9016
PBAR2           -0.4030625 1.89573326805783648474346                  -0.2126156 0.8316
PBAR3            4.9944712 1.92647883333679281747663                   2.5925388 0.0095
CA2             -1.6169522 1.21567616898678765302577                  -1.3300846 0.1835
CA3            -47.7908405 0.00000000000000146167712   -32695894135736532.0000000 0.0000
GENREHomme       1.6147270 1.33310394915002139448745                   1.2112536 0.2258
STATUSOui      -88.5386473 0.00000000000000007913076 -1118890340010134656.0000000 0.0000
ALTRUISMOui      5.1330843 2.38113268101432096202075                   2.1557322 0.0311
HEALTHISSUEOui  94.6255693 0.00000000000000004884390  1937305769113789184.0000000 0.0000
1|2              4.8484650 2.47604347822508996657120                   1.9581502 0.0502
2|3              8.1257132 3.06235992037748072647219                   2.6534155 0.0080
```

Figure 6.14: Regression with 3 threshold of WTP and the polr function 1

```
> model_polr <- polr(WTP_3 ~ ENV+PT+PB+PBAR+CA+GENRE+STATUS+ALTRUISM+HEALTHISSUE, data=base, method = c("logisti
c"))
Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
> summary(model_polr)

Re-fitting to get Hessian

Call:
polr(formula = WTP_3 ~ ENV + PT + PB + PBAR + CA + GENRE + STATUS +
    ALTRUISM + HEALTHISSUE, data = base, method = c("logistic"))

Coefficients:
                  Value             Std. Error                 t value
ENV2             3.6117 1.87699948980030995038                  1.9242
PT2             -0.2210 1.40005457590449466920                 -0.1579
PB2              0.2133 1.72562867832402311308                  0.1236
PBAR2           -0.4031 1.89573326805783648474                 -0.2126
PBAR3            4.9945 1.92647883333679281748                  2.5925
CA2             -1.6170 1.21567616898678765303                 -1.3301
CA3            -47.7908 0.00000000000000146168   -32695894135736532.0000
GENREHomme       1.6147 1.33310394915002139449                  1.2113
STATUSOui      -88.5386 0.00000000000000007913 -1118890340010134656.0000
ALTRUISMOui      5.1331 2.38113268101432096202                  2.1557
HEALTHISSUEOui  94.6256 0.00000000000000004884  1937305769113789184.0000

Intercepts:
    Value                  Std. Error               t value
1|2                 4.8485                   2.4760                   1.9582
2|3                 8.1257                   3.0624                   2.6534

Residual Deviance: 30.04745
AIC: 56.04745
> (ctable<-coef(summary(model_polr)))

Re-fitting to get Hessian

                    Value                Std. Error                    t value
ENV2             3.6116674 1.87699948980030995038248                  1.9241707
PT2             -0.2210074 1.40005457590449466920290                 -0.1578563
PB2              0.2133231 1.72562867832402311307760                  0.1236205
PBAR2           -0.4030625 1.89573326805783648474346                 -0.2126156
PBAR3            4.9944712 1.92647883333679281747663                  2.5925388
CA2             -1.6169522 1.21567616898678765302577                 -1.3300846
CA3            -47.7908405 0.00000000000000146167712   -32695894135736532.0000000
GENREHomme       1.6147270 1.33310394915002139448745                  1.2112536
STATUSOui      -88.5386473 0.00000000000000007913076 -1118890340010134656.0000000
ALTRUISMOui      5.1330843 2.38113268101432096202075                  2.1557322
HEALTHISSUEOui  94.6255693 0.00000000000000004884390  1937305769113789184.0000000
1|2              4.8484650 2.47604347822508996657120                  1.9581502
2|3              8.1257132 3.06235992037748072647219                  2.6534155
> p <- pnorm(abs(ctable[,"t value"]),lower.tail=FALSE)*2
> p2<-round(p,4)
> (ctable<-cbind(ctable,pvalue=p2))
                    Value                Std. Error                    t value pvalue
ENV2             3.6116674 1.87699948980030995038248                  1.9241707 0.0543
PT2             -0.2210074 1.40005457590449466920290                 -0.1578563 0.8746
PB2              0.2133231 1.72562867832402311307760                  0.1236205 0.9016
PBAR2           -0.4030625 1.89573326805783648474346                 -0.2126156 0.8316
PBAR3            4.9944712 1.92647883333679281747663                  2.5925388 0.0095
CA2             -1.6169522 1.21567616898678765302577                 -1.3300846 0.1835
CA3            -47.7908405 0.00000000000000146167712   -32695894135736532.0000000 0.0000
GENREHomme       1.6147270 1.33310394915002139448745                  1.2112536 0.2258
STATUSOui      -88.5386473 0.00000000000000007913076 -1118890340010134656.0000000 0.0000
ALTRUISMOui      5.1330843 2.38113268101432096202075                  2.1557322 0.0311
HEALTHISSUEOui  94.6255693 0.00000000000000004884390  1937305769113789184.0000000 0.0000
1|2              4.8484650 2.47604347822508996657120                  1.9581502 0.0502
2|3              8.1257132 3.06235992037748072647219                  2.6534155 0.0080
```

Figure 6.15: Regression with 3 threshold of WTP and the function 2

```
                          Value   Std. Error       t value pvalue
PT2                   1.1684076 1.428571e+00  8.178855e-01 0.4134
PB2                   0.8274193 1.608085e+00  5.145370e-01 0.6069
SE2                  -0.9097024 1.879690e+00 -4.839641e-01 0.6284
SE3                   0.1532299 1.777146e+00  8.622249e-02 0.9313
CA2                  -0.8169871 1.118436e+00 -7.304732e-01 0.4651
CA3                 -97.9128148          NaN           NaN    NaN
GENREHomme            1.6464098 1.202417e+00  1.369250e+00 0.1709
MAISONOui            -0.2274233 1.094393e+00 -2.078077e-01 0.8354
ALTRUISMOui           3.1849080 2.215812e+00  1.437355e+00 0.1506
HEALTHISSUE_recOui   60.6463440 6.639759e-16  9.133817e+16 0.0000
ENV2                  1.7455927 1.457213e+00  1.197899e+00 0.2310
1|2                   4.0272853 2.674140e+00  1.506012e+00 0.1321
2|3                   5.9504224 2.830021e+00  2.102607e+00 0.0355
```

Figure 6.16: Regression resulting from the step wise selection

```
> model_clm_step <- clm(WTP_5 ~  PB + PBAR + STATUS + HEALTHISSUE, data=base)
> summary(model_clm_step)
formula: WTP_5 ~ PB + PBAR + STATUS + HEALTHISSUE
data:    base


Coefficients:
              Estimate Std. Error z value Pr(>|z|)
PB2            -1.4301     0.8168  -1.751  0.07997 .
PBAR2           2.0082     0.9960   2.016  0.04377 *
PBAR3           1.8548     1.0010   1.853  0.06390 .
STATUSOui      -3.6664     1.2166  -3.014  0.00258 **
HEALTHISSUEOui   4.2846     1.6523   2.593  0.00951 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Threshold coefficients:
    Estimate Std. Error z value
1|2  -2.2757     0.8008  -2.842
2|3   0.2007     0.6412   0.313
3|4   1.3132     0.6937   1.893
4|5   3.1394     0.9559   3.284
> coef(summary(model_clm_step))
                 Estimate Std. Error    z value    Pr(>|z|)
1|2            -2.2756653  0.8008253 -2.8416502 0.004488071
2|3             0.2007488  0.6412155  0.3130754 0.754223368
3|4             1.3132248  0.6936971  1.8930811 0.058347092
4|5             3.1394356  0.9559108  3.2842348 0.001022597
PB2            -1.4301318  0.8168226 -1.7508474 0.079972205
PBAR2           2.0081650  0.9959639  2.0163030 0.043768306
PBAR3           1.8547572  1.0010188  1.8528696 0.063901050
STATUSOui      -3.6663529  1.2165626 -3.0136984 0.002580842
HEALTHISSUEOui  4.2846462  1.6522580  2.5932065 0.009508566
```

Figure 6.17: R2 McFadden

```
> pseudo_R2 <- pR2(model_clm_step)
fitting null model for pseudo-r2
> pseudo_R2
        llh     llhNull          G2    McFadden        r2ML        r2CU
-40.3681540 -48.2405290  15.7447500   0.1631901   0.3886120   0.4086541
```

Figure 6.18: Odd-ratio

```
> pseudo_R2 <- pR2(model_clm_step)
fitting null model for pseudo-r2
> pseudo_R2
        llh     llhNull          G2    McFadden        r2ML        r2CU
-40.3681540 -48.2405290  15.7447500   0.1631901   0.3886120   0.4086541
```

Figure 6.19: Testing the proportional odds assumption with vglm

```
> fitmodel <- vglm(WTP_5 ~ PB + PBAR + STATUS + HEALTHISSUE, data=base, li
nk="logit", family=cumulative(parallel=TRUE,reverse=TRUE))
> fitmodel1 <- vglm(WTP_5 ~ PB + PBAR + STATUS + HEALTHISSUE, data=base, l
ink="logit", family=cumulative(parallel=FALSE~1+PB,reverse=TRUE))
> 1-pchisq(deviance(fitmodel)-deviance(fitmodel1), df=df.residual(fitmode
l)- df.residual(fitmodel1))
[1] 0.4135558
> fitmodel2 <- vglm(WTP_5 ~ PB + PBAR + STATUS + HEALTHISSUE, data=base, l
ink="logit", family=cumulative(parallel=FALSE~1+PBAR,reverse=TRUE))
> 1-pchisq(deviance(fitmodel)-deviance(fitmodel2), df=df.residual(fitmode
l)- df.residual(fitmodel2))
[1] 0.266545
> fitmodel3 <- vglm(WTP_5 ~ PB + PBAR + STATUS + HEALTHISSUE, data=base, l
ink="logit", family=cumulative(parallel=FALSE~1+STATUS,reverse=TRUE))
> 1-pchisq(deviance(fitmodel)-deviance(fitmodel3), df=df.residual(fitmode
l)- df.residual(fitmodel3))
[1] 0.6916909
> fitmodel4 <- vglm(WTP_5 ~ PB + PBAR + STATUS + HEALTHISSUE, data=base, l
ink="logit", family=cumulative(parallel=FALSE~1+HEALTHISSUE,reverse=TRUE))
Warning: fitted values close to 0 or 1Warning: fitted values close to 0 or
1Error in tapplymat1(ccump, "diff") :
  NA/NaN/Inf in foreign function call (arg 1)
```

Figure 6.20: Health issue problems when testing for heteroscedasticity

```
> results.oprob <- oglmx(WTP_5~ PB + PBAR + STATUS + HEALTHISSUE, ~ PB + PBAR + STATUS + HEALTHISSUE, data=base, link="logit", co
nstantMEAN=FALSE, constantSD=FALSE, delta=0)
Warning: using type = "numeric" with a factor response will be ignored
> summary(results.oprob)
Heteroskedastic Ordered Logit Regression
Log-Likelihood: -35.06341
No. Iterations: 40
McFadden's R2: 0.2731546
AIC: 96.12681
----- Mean Equation ------
                Estimate Std. error t value Pr(>|t|)
PB2             -0.99360    0.86844 -1.1441 0.252574
PBAR2            1.36895    0.90243  1.5170 0.129277
PBAR3            1.36895    0.90243  1.5170 0.129277
STATUSOui       -2.15903    0.82276 -2.6241 0.008687 **
HEALTHISSUEOui -83.73489        NaN     NaN      NaN
----- SD Equation ------
                Estimate Std. error t value Pr(>|t|)
PBAR2           -0.34430    0.47020 -0.7322   0.4640
PBAR3            0.21952    0.65392  0.3357   0.7371
STATUSOui      -17.34677  736.89804 -0.0235   0.9812
HEALTHISSUEOui  18.87321        NaN     NaN      NaN
----- Threshold Parameters -----
                 Estimate Std. error t value Pr(>|t|)
Threshold (1->2) -1.78368    0.79637 -2.2398  0.02511 *
Threshold (2->3)  0.14098    0.63283  0.2228  0.82371
Threshold (3->4)  1.20131    0.73009  1.6454  0.09988 .
Threshold (4->5)  3.81814    1.84191  2.0729  0.03818 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Figure 6.21: Testing for heteroscedasticity

```
> summary(results.oprob)
Heteroskedastic Ordered Logit Regression
Log-Likelihood: -37.76817
No. Iterations: 36
McFadden's R2: 0.2170863
AIC: 99.53634
----- Mean Equation ------
              Estimate Std. error t value Pr(>|t|)
PB2           -0.98250    0.68431 -1.4358  0.15107
PBAR2          1.45633    0.79235  1.8380  0.06607 .
PBAR3          1.45633    0.79235  1.8380  0.06607 .
STATUSOui     -2.08639    0.81570 -2.5578  0.01053 *
HEALTHISSUEOui 1.45633    0.79235  1.8380  0.06607 .
----- SD Equation ------
          Estimate Std. error t value Pr(>|t|)
PBAR2     -0.49332    0.47792 -1.0322   0.3020
PBAR3     -0.28776    0.54732 -0.5258   0.5990
STATUSOui -17.72552  532.71213 -0.0333   0.9735
----- Threshold Parameters -----
                Estimate Std. error t value Pr(>|t|)
Threshold (1->2) -1.61257    0.74772 -2.1567 0.031032 *
Threshold (2->3)  0.17321    0.59414  0.2915 0.770639
Threshold (3->4)  1.03878    0.65065  1.5965 0.110374
Threshold (4->5)  2.34487    0.86359  2.7152 0.006623 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 6.22: Testing for heteroscedasticity

```
> margins.oglmx(results.oprob, atmeans=TRUE)
Marginal Effects on Pr(Outcome==1)
                            Marg. Eff             Std. error t value            Pr(>|t|)
PB2             0.0000000000302138743  0.0000000609183116534  0.0005              0.9996
PBAR2          -0.0000000043506455449  0.0000069722194508821 -0.0006              0.9995
PBAR3          -0.0000000000055696373  0.0000000120135874165 -0.0005              0.9996
STATUSOui       0.9215508125912987847  0.0516805152266419238 17.8317 <0.0000000000000002 ***
HEALTHISSUEOui -0.0000000000000061191  0.0000000000148809150 -0.0004              0.9997
------------------------------------
Marginal Effects on Pr(Outcome==2)
                 Marg. Eff  Std. error  t value             Pr(>|t|)
PB2             0.99971385  0.19822738   5.0433         0.0000004576 ***
PBAR2          -0.99997988  0.01811499 -55.2018 < 0.00000000000000022 ***
PBAR3          -0.99960593  0.25702656  -3.8891            0.0001006 ***
STATUSOui      -0.36417826  0.10107083  -3.6032            0.0003143 ***
HEALTHISSUEOui -0.00029218  0.12659544  -0.0023            0.9981585
------------------------------------
Marginal Effects on Pr(Outcome==3)
                 Marg. Eff  Std. error t value  Pr(>|t|)
PB2            -0.99959856  0.28521756 -3.5047 0.0004571 ***
PBAR2           0.80540086 18.66635103  0.0431 0.9655842
PBAR3           0.01130393  4.01565878  0.0028 0.9977540
STATUSOui      -0.25833256  0.09201088 -2.8076 0.0049907 **
HEALTHISSUEOui  0.00029218  0.12659543  0.0023 0.9981585
------------------------------------
Marginal Effects on Pr(Outcome==4)
                        Marg. Eff          Std. error t value Pr(>|t|)
PB2            -0.0001152835960104  0.0870130515017200 -0.0013 0.998943
PBAR2           0.1945790188662109 18.6483620584664749  0.0104 0.991675
PBAR3           0.9883020024077688  4.2724893839095461  0.2313 0.817068
STATUSOui      -0.2221326119140572  0.0846963337626150 -2.6227 0.008724 **
HEALTHISSUEOui  0.0000000000093403  0.0000000170574127  0.0005 0.999563
------------------------------------
Marginal Effects on Pr(Outcome==5)
                              Marg. Eff                  Std. error t value Pr(>|t|)
PB2            -0.0000000000000000066613381  0.0000000000163092809830 -0.0004   0.9997
PBAR2           0.0000000000000000000000000  0.0000000000017203871127  0.0000   1.0000
PBAR3           0.0000000000000042765790909  0.0000000101368671016402  0.0004   0.9997
STATUSOui      -0.0769073865395742961581 5  0.0521939476869154178606 5 -1.4735   0.1406
HEALTHISSUEOui  0.0000000000000000000000000  0.0000000000000000000018021  0.0000   1.0000
```

6.2.2 Logit

Figure 6.23: R output

```
> modele <- glm(WTP ~ PB + PBAR + STATUS, data=base, family = binomial(link="logit"))
Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
> summary(modele)

Call:
glm(formula = WTP ~ PB + PBAR + STATUS, family = binomial(link = "logit"),
    data = base)

Deviance Residuals:
          Min            1Q        Median            3Q           Max
-0.0000116683  0.0000000211  0.0000026338  0.0000039686  0.0000085114

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)    26.387  94882.780       0        1
PB2            -1.526 104931.138       0        1
PBAR2          47.452 116162.496       0        1
PBAR3          47.539 128380.404       0        1
STATUSOui     -48.272  97928.077       0        1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 8.89989110110342  on 31  degrees of freedom
Residual deviance: 0.00000000052848  on 27  degrees of freedom
AIC: 10

Number of Fisher Scoring iterations: 25

>
```

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Acronyms

CA Cues to action

CVM Contingent Valuation Method

GHG Green Houses Gases

HBM Health Belief Model

HCPC Hieratchical Clustering on Principle components

HWs Heatwaves

IPCC Intergovernmental Panel on Climate Change

MCA Multiple correspondance analysis

MMs Mitigation measures

PB Perceived Benefits

PBARs Perceived Barriers

PNV Potential Natural Vegetation

PT Perceived Threat

SE Self Efficacy

UHI Urban Heat Island

UMF Urban Micro Forest

WTP Willingness to Pay

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Contents

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